ECON 121 FA25 Final Exam

Solution

Question 1

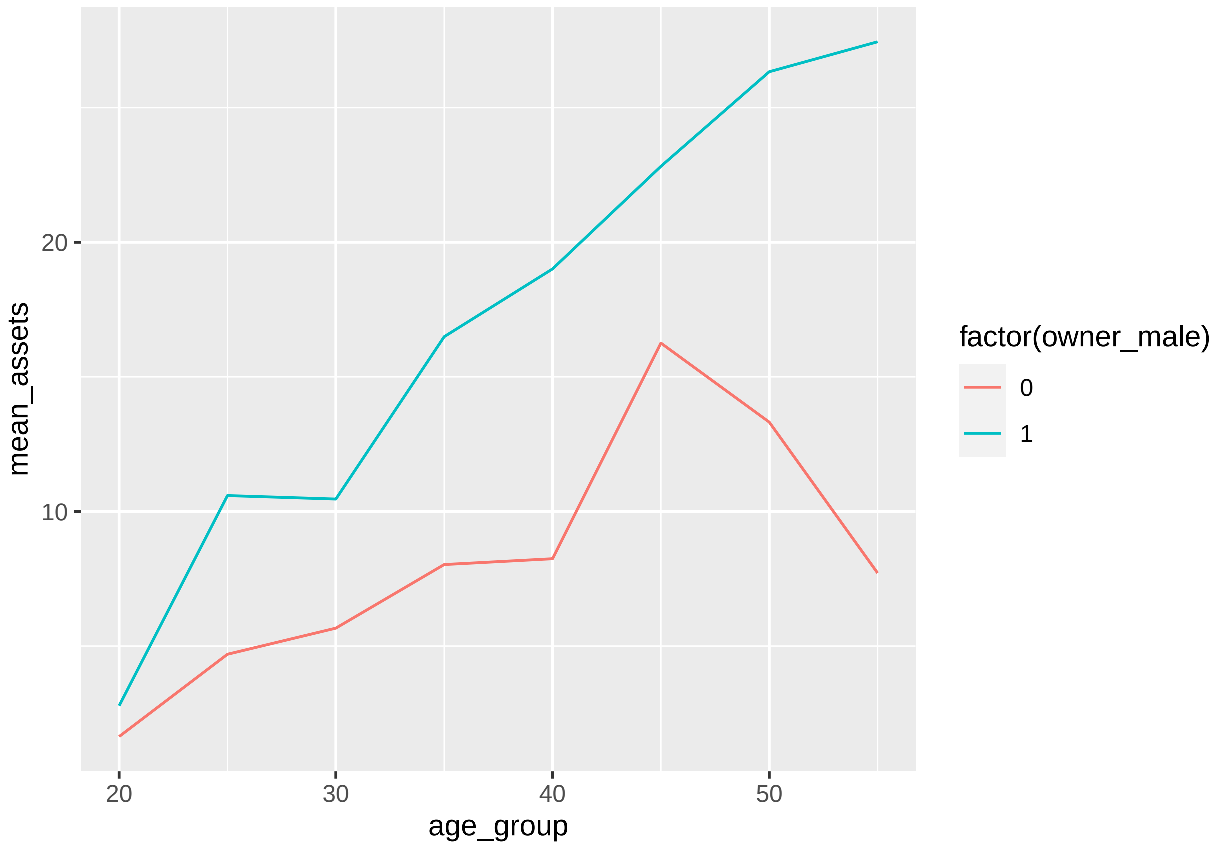
```r
# 98% of owners are between 20 and 59, so I will focus on these ages.
# You could have made a different choice here.
finance |>
  mutate(age20to59 = if_else(owner_age>=20&owner_age<60,1,0)) |>
  count(age20to59) |>
  mutate(pct = n/sum(n))
```

```
## # A tibble: 2 x 3
##   age20to59     n    pct
##       <dbl> <int>  <dbl>
## 1         0   115 0.0224
## 2         1  5019 0.978
```

```r
# Generate a table with average assets for men and women in each
# 5-year age group.
table <-
  finance |>
  filter(owner_age>=20&owner_age<60) |>
  mutate(age_group = floor(owner_age/5)*5) |>
  group_by(owner_male, age_group) |>
  summarise(mean_assets = mean(assets))
```

```
## `summarise()` has grouped output by 'owner_male'. You can override using the
## `.groups` argument.
```

```r
# Graph the table using ggplot.
ggplot(table, aes(x = age_group, y = mean_assets, color = factor(owner_male))) +
  geom_line()
```



Question 2

```r
# First run the regression, saving results so we can use them again later.
# Standard errors are clustered at the town level because towns were sampled,
# and errors may be correlated within towns. The question asked to use pre-
# intervention data, so we subset to round 1.
model_q1 <- feols(assets ~ owner_male + owner_age,
      data = finance,
      subset = ~(round==1),
      vcov = ~townid)

# Now report the results.
summary(model_q1)
```

```
## OLS estimation, Dep. Var.: assets
## Observations: 2,567
## Subset: (round == 1)
## Standard-errors: Clustered (townid)
##               Estimate Std. Error  t value   Pr(>|t|)
## (Intercept) -12.228567   4.491489 -2.72261 8.0079e-03 **
## owner_male    6.706359   3.072382  2.18279 3.2099e-02 *
## owner_age     0.517575   0.120757  4.28609 5.2089e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 46.6   Adj. R2: 0.016029
```

Question 3

```r
# Use the hypotheses function to test the null that the coefficient on male
# is the same as 25 times the coefficient on owner_age.
hypotheses(model_q1, "owner_male - 25*owner_age = 0")
```

```
##
##                              Term Estimate Std. Error     z Pr(>|z|)   S 2.5 %
##  owner_male - 25*owner_age = 0    -6.23       2.72 -2.29   0.0221 5.5 -11.6
##  97.5 %
##  -0.894
##
## Columns: term, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high
```

Question 4

Assets are higher for male owners than female owners: 6.7 wan, controlling for age. Assets are also significantly higher for older owners: 0.52 wan for each additional year of age, controlling for gender. The results from Question 3 indicate that the gap between 50- and 25-year olds is 6.23 wan larger than the gap between men and women. All of these quantities are significantly different from zero at the 5% level (although the question did not ask).

Question 5

```r
# To estimate the effect of loan outreach on loan takeup, we regress loan_any
# on officer as well as town fixed effects. We need the town fixed effects
# because the probability of being randomly assigned an officer differed
# between towns. We use round 2 data because loan outreach could not have an
# effect on loan takeup before the intervention occurred.
feols(loan_any ~ officer | townid,
      data = finance,
      subset = ~(round==2),
      vcov = ~townid)
```

```
## OLS estimation, Dep. Var.: loan_any
## Observations: 2,567
## Subset: (round == 2)
## Fixed-effects: townid: 78
## Standard-errors: Clustered (townid)
##         Estimate Std. Error t value   Pr(>|t|)
## officer 0.226989   0.041374  5.4863 5.0452e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 0.350269     Adj. R2: 0.25037
##                  Within R2: 0.041932
```

Question 6

Loan outreach increases loan takeup by 22 percentage points. The t-statistic is 5.5, and the p-value is < 0.01, so the estimated effect is highly statistically significant. The number of clusters is large, so we can rely on the Central Limit Theorem and do not need to assume normal errors. You got full credit if you reasoned that the sample size or number of observations is large. With clustered standard, it is really the number of clusters that matters, but this is a nuanced point.

Question 7

```r
# Because we want results in terms of odds, we use a logit model.
# First estimate the model and save the results. Because we are interested
# in loan takeup *after* an officer visit, we focus on observations with
# round==1 and officer==1.
logit_model <- feglm(loan_any ~ owner_male + owner_age + owner_college,
      data = finance,
      subset = ~(round==2 & officer==1),
      vcov = ~townid,
      family = 'logit')

# To obtain results in terms of probabilities, we compute average marginal
# effects.
avg_slopes(logit_model)
```

```
##
##           Term Contrast Estimate Std. Error     z Pr(>|z|)   S    2.5 %  97.5 %
##  owner_age        dY/dX  0.00406    0.00265 1.533   0.1253 3.0 -0.00113 0.00924
##  owner_college    1 - 0  0.01655    0.04079 0.406   0.6849 0.5 -0.06340 0.09650
##  owner_male       1 - 0  0.09583    0.04426 2.165   0.0304 5.0  0.00908 0.18258
##
## Columns: term, contrast, estimate, std.error, statistic, p.value, s.value, conf.low, conf.high
## Type:  response
```

```r
# To obtain results in terms of odds, we compute odds rations.
oddsratio <- exp(coef(logit_model))
ci <- exp(confint(logit_model))
cbind(oddsratio, ci)
```

```
##                 oddsratio      2.5 %    97.5 %
## (Intercept)   0.2633234 0.09372488 0.7398162
## owner_male    1.5009241 1.02206101 2.2041474
## owner_age     1.0173748 0.99482156 1.0404393
## owner_college 1.0725287 0.76502513 1.5036340
```

Question 8

Interpret the coefficient and odds ratio on male. 0.095 percentage points. 56 percent higher odds. No collateral requirements, so women weren't disadvantaged. But men still took out more.

The average marginal effect on `owner_male` is 0.096, so male owners are 10 percentage points more likely to take up loans than female owners. This estimate is significantly different from 0 with $p < 0.05$, so we can reject the null hypothesis that gender is not associated with takeup. The odds ration is 1.50, so male owners have 50% higher odds of takeup than female owners. This 95% confidence interval excludes 1, so we can reject the null hypothesis that gender is not associated with takeup.

Question 9

```r
# Here again, we use round 2 data, after any outreach occurred. We
# use the same basic structure as in Question 5, just substituting assets
# for takeup as the dependent variable.
feols(assets ~ officer | townid,
      data = finance,
      subset = ~(round==2),
```

```r
      vcov = ~townid)
```

```
## OLS estimation, Dep. Var.: assets
## Observations: 2,567
## Subset: (round == 2)
## Fixed-effects: townid: 78
## Standard-errors: Clustered (townid)
##         Estimate Std. Error t value  Pr(>|t|)
## officer  8.64365    2.99716 2.88395 0.0050899 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 42.9     Adj. R2: 0.233314
##              Within R2: 0.004222
```

Question 10

Loan outreach raises assets by 8.6 wan. The estimated effect is statistically significant, with $p < 0.01$. The estimated effect is slightly larger than the male-female gap of 6.7 that we estimated in Question 2. Because we ran both regressions in the same dataset, the estimates from may have non-zero covariances, so we cannot test for differences in coefficients across regressions using just the point estimates and standard errors.

Question 11

```r
# We rerun the regression from Question 9 using round 1  instead of round 2.
feols(assets ~ officer | townid,
      data = finance,
      subset = ~(round==1),
      vcov = ~townid)
```

```
## OLS estimation, Dep. Var.: assets
## Observations: 2,567
## Subset: (round == 1)
## Fixed-effects: townid: 78
## Standard-errors: Clustered (townid)
##         Estimate Std. Error  t value Pr(>|t|)
## officer  2.38497    4.56309 0.522666  0.60271
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 41.0     Adj. R2: 0.216136
##              Within R2: 3.523e-4
```

Question 12

Baseline assets did not differ significantly: the point estimate is close to 0 and smaller than its standard error. This is called a balance check (or falsification check or placebo check). It suggests that randomization within towns was executed correctly.

Question 13

```r
# We can interact officer with owner_male to estimate heterogeneous effects
# by gender.
feols(assets ~ officer*owner_male | townid,
      data = finance,
```

```r
      subset = ~(round==2),
      vcov = ~townid)
```

```
## OLS estimation, Dep. Var.: assets
## Observations: 2,567
## Subset: (round == 2)
## Fixed-effects: townid: 78
## Standard-errors: Clustered (townid)
##                    Estimate Std. Error   t value Pr(>|t|)
## officer             4.203250    2.32288  1.809497 0.074276 .
## owner_male         -0.716460    2.03574 -0.351941 0.725844
## officer:owner_male  8.142273    3.83818  2.121388 0.037107 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 42.8     Adj. R2: 0.234912
##              Within R2: 0.007096
```

Question 14

The coefficient on the interaction term is 8.14, implying that male-owned firms have an 8 wan larger effect than female-owned firms. This difference has a t-statistic of 2.12 p-value of 0.037, so it is statistically significant. Loan outreach increased asset inequality between male- and female-owned firms: male-owned firms already had more assets, and loan outreach increased this gender gap. We can obtain the point estimate of the difference from running separate regressions for men and women, but we cannot obtain the standard error of the difference. That's because men and women come from the same towns, and errors may be correlated within town.

Question 15

```r
# Reduced form divided by the first stage
8.64365 / 0.226989
```

```
## [1] 38.0796
```

Question 16

```r
# To estimate it using two-stage least squares, we run:
feols(assets ~ factor(townid) | loan_any ~ officer,
      data = finance,
      subset = ~(round==2),
      vcov = ~townid)
```

```
## TSLS estimation, Dep. Var.: assets, Endo.: loan_any, Instr.: officer
## Second stage: Dep. Var.: assets
## Observations: 2,567
## Subset: (round == 2)
## Standard-errors: Clustered (townid)
##                   Estimate Std. Error   t value   Pr(>|t|)
## (Intercept)      -9.095653   4.729105 -1.923335 5.8135e-02 .
## fit_loan_any     38.079568  14.975500  2.542791 1.3003e-02 *
## factor(townid)2  15.118245   3.769137  4.011062 1.3887e-04 ***
## factor(townid)3  14.863022   1.297620 11.454061  < 2.2e-16 ***
## factor(townid)4 195.581573   2.402085 81.421582  < 2.2e-16 ***
## factor(townid)5 121.397225   3.577144 33.936916  < 2.2e-16 ***
```

```
## factor(townid)6  113.877058   3.199101  35.596586  < 2.2e-16 ***
## factor(townid)7   76.455786   0.121259 630.515828  < 2.2e-16 ***
## factor(townid)8   12.443479   4.729105   2.631255 1.0272e-02 *
## factor(townid)9   14.431915   1.542829   9.354192 2.4950e-14 ***
## factor(townid)10  16.903653   4.729105   3.574387 6.1003e-04 ***
## factor(townid)11  14.339145   4.729105   3.032105 3.3081e-03 **
## factor(townid)12  14.476454   4.335013   3.339426 1.2962e-03 **
## factor(townid)13   3.891353   0.262728  14.811332  < 2.2e-16 ***
## factor(townid)14  31.970653   4.729105   6.760402 2.3544e-09 ***
## factor(townid)15  55.032320   4.729105  11.636941  < 2.2e-16 ***
## factor(townid)16  30.300064   3.998593   7.577682 6.5882e-11 ***
## factor(townid)17  20.732320   4.729105   4.383984 3.6437e-05 ***
## factor(townid)18  -4.030264   0.619288  -6.507904 6.9921e-09 ***
## factor(townid)19  11.404320   4.729105   2.411517 1.8269e-02 *
## factor(townid)20   5.696074   0.324546  17.550876  < 2.2e-16 ***
## factor(townid)21  -0.782697   2.216054  -0.353194 7.2491e-01
## factor(townid)22  57.518598   3.279863  17.536889  < 2.2e-16 ***
## factor(townid)23  24.476764   4.729105   5.175771 1.7576e-06 ***
## factor(townid)24  14.438103   4.121990   3.502702 7.7028e-04 ***
## factor(townid)25  12.521740   4.729105   2.647803 9.8230e-03 **
## factor(townid)26  16.322576   4.729105   3.451515 9.0827e-04 ***
## factor(townid)27  10.554214   1.273221   8.289384 2.8162e-12 ***
## factor(townid)28 -19.464023   6.502520  -2.993305 3.7082e-03 **
## factor(townid)29  20.537220   4.573110   4.490865 2.4549e-05 ***
## factor(townid)30  52.672276   0.556365  94.672107  < 2.2e-16 ***
## factor(townid)31   9.321783   0.236455  39.423030  < 2.2e-16 ***
## factor(townid)32  16.700557   1.134985  14.714338  < 2.2e-16 ***
## factor(townid)33  11.231074   0.324546  34.605446  < 2.2e-16 ***
## factor(townid)34  23.964172   4.729105   5.067380 2.6978e-06 ***
## factor(townid)35   1.432242   4.729105   0.302857 7.6282e-01
## factor(townid)36  -4.235887   4.102600  -1.032489 3.0508e-01
## factor(townid)37  18.805653   4.729105   3.976577 1.5664e-04 ***
## factor(townid)38   6.233308   3.867941   1.611531 1.1116e-01
## factor(townid)39  -2.328217   0.236455  -9.846334 2.8411e-15 ***
## factor(townid)40  15.655298   4.630582   3.380849 1.1375e-03 **
## factor(townid)41  13.175031   1.520070   8.667387 5.2523e-13 ***
## factor(townid)42   5.101323   0.050310 101.398538  < 2.2e-16 ***
## factor(townid)43  11.344837   4.729105   2.398939 1.8862e-02 *
## factor(townid)44  13.016333   1.256526  10.358988 3.0010e-16 ***
## factor(townid)45  19.130163   0.049262 388.338933  < 2.2e-16 ***
## factor(townid)46  -0.870104   2.045526  -0.425369 6.7175e-01
## factor(townid)47  10.530813   0.805319  13.076579  < 2.2e-16 ***
## factor(townid)48  23.170612   0.262728  88.192375  < 2.2e-16 ***
## factor(townid)49  17.903653   4.729105   3.785844 3.0163e-04 ***
## factor(townid)50   5.108540   2.857168   1.787974 7.7714e-02 .
## factor(townid)51   8.736582   4.048401   2.158033 3.4042e-02 *
## factor(townid)52   8.541429   2.589748   3.298170 1.4748e-03 **
## factor(townid)53   3.726903   2.101825   1.773175 8.0154e-02 .
## factor(townid)54  24.097065   0.886707  27.175898  < 2.2e-16 ***
## factor(townid)55  11.084670   4.729105   2.343925 2.1663e-02 *
## factor(townid)56   0.714919   1.926672   0.371064 7.1161e-01
## factor(townid)57  15.325761   0.985230  15.555512  < 2.2e-16 ***
## factor(townid)58   4.274148   0.886707   4.820248 7.0592e-06 ***
## factor(townid)59  39.568883   4.194266   9.434043 1.7524e-14 ***
```

```
## factor(townid)60   7.089970   3.659427   1.937454 5.6357e-02 .
## factor(townid)61  12.502320   4.729105   2.643697 9.9327e-03 **
## factor(townid)62   0.705329   0.932364   0.756495 4.5166e-01
## factor(townid)63   6.044696   3.231555   1.870522 6.5211e-02 .
## factor(townid)64  12.779739   1.734005   7.370070 1.6440e-10 ***
## factor(townid)65  20.461613   0.584782  34.990165  < 2.2e-16 ***
## factor(townid)66   9.012812   2.911456   3.095638 2.7384e-03 **
## factor(townid)67  27.872696   3.231555   8.625165 6.3361e-13 ***
## factor(townid)68  -8.780643   3.084199  -2.846977 5.6553e-03 **
## factor(townid)69  23.598638   4.324362   5.457138 5.6795e-07 ***
## factor(townid)70  24.585653   4.729105   5.198796 1.6039e-06 ***
## factor(townid)71  -8.244131   2.758645  -2.988472 3.7611e-03 **
## factor(townid)72  16.057875   4.729105   3.395542 1.0858e-03 **
## factor(townid)73  17.767428   0.985230  18.033782  < 2.2e-16 ***
## factor(townid)74   3.249739   1.734005   1.874123 6.4707e-02 .
## factor(townid)75   5.869826   1.261095   4.654548 1.3285e-05 ***
## factor(townid)76 -14.083215   4.386416  -3.210642 1.9328e-03 **
## factor(townid)77  12.338100   4.345118   2.839532 5.7759e-03 **
## factor(townid)78  14.890098   4.729105   3.148608 2.3348e-03 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 44.1   Adj. R2: 0.187923
## F-test (1st stage), loan_any: stat = 108.9    , p < 2.2e-16, on 1 and 2,488 DoF.
##                  Wu-Hausman: stat =   6.58014, p = 0.01037, on 1 and 2,487 DoF.
```

```
# The first line could have also been:
# assets ~ 1 | townid | loan_any ~ officer
```

Question 17

We should characterize the estimated effect from Question 16 as a LATE because always takers exist. The key line in the description of the setting is: "All firms could apply for the new loan product, but the bank randomly chose a subset of firms to be visited by a loan officer." So firms in the control group could still access the new loan product. In the data, some firms in the control group did take out loans, and you could have checked this too. For the LATE interpretation, we need the instrument to be relevant (which we showed in Question 5). We also need to assume that loan outreach was randomly assigned (independence), that loan outreach only affects assets through loan takeup (exclusion restriction), and that loan outreach does not reduce loan takeup for any firm (monotonicity). Under these assumptions, the estimated effect represents the average among firms who were induced to borrow by the loan officer.

Question 18

We could have also included owner characteristics as well as wave 1 outcomes. These covariates are not necessary for causal identification. Officers were randomly assigned within towns, so only town dummies are required. The additional covariates can help assess robustness (to check that randomization was successful) or to increase precision (by absorbing residual variance). We mainly talked about the first one in class, so you did not have to mention both.

Question 19

```
# Under a parallel trends assumption, we can estimate a difference-in-
# differences model. This model would have a dummy for ever receiving a new
# loan, a dummy for round 2, and the interaction of these two dummies.
feols(assets ~ loan_any*round,
```

```r
      data = finance,
      vcov = ~townid)
```

```
## OLS estimation, Dep. Var.: assets
## Observations: 5,134
## Standard-errors: Clustered (townid)
##                Estimate Std. Error   t value  Pr(>|t|)
## (Intercept)     7.72328    2.86459  2.696116 0.0086124 **
## loan_any       -1.00594    5.08604 -0.197784 0.8437352
## round           2.74371    1.27792  2.147012 0.0349398 *
## loan_any:round  6.18986    3.13461  1.974681 0.0518896 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 48.3   Adj. R2: 0.00681
```

Question 20

```r
# We can estimate the effect per wan lent by running a two-stage least squares
# regression, changing the endogenous variable from loan_any to loan_amount:
feols(assets ~ factor(townid) | loan_amount ~ officer,
      data = finance,
      subset = ~(round==2),
      vcov = ~townid)
```

```
## TSLS estimation, Dep. Var.: assets, Endo.: loan_amount, Instr.: officer
## Second stage: Dep. Var.: assets
## Observations: 2,567
## Subset: (round == 2)
## Standard-errors: Clustered (townid)
##                    Estimate Std. Error    t value   Pr(>|t|)
## (Intercept)       -5.458414   3.061235  -1.783076 7.8515e-02 .
## fit_loan_amount    1.285241   0.469060   2.740034 7.6316e-03 **
## factor(townid)2   12.274259   2.459876   4.989789 3.6574e-06 ***
## factor(townid)3   13.259216   1.789534   7.409313 1.3834e-10 ***
## factor(townid)4  182.964999   6.833701  26.773924  < 2.2e-16 ***
## factor(townid)5  117.426649   1.870544  62.776751  < 2.2e-16 ***
## factor(townid)6  109.911339   4.416136  24.888576  < 2.2e-16 ***
## factor(townid)7   77.417080   0.463363 167.076495  < 2.2e-16 ***
## factor(townid)8    8.806240   3.061235   2.876695 5.1965e-03 **
## factor(townid)9   11.349340   0.306754  36.998206  < 2.2e-16 ***
## factor(townid)10  13.266414   3.061235   4.333681 4.3805e-05 ***
## factor(townid)11  10.701906   3.061235   3.495944 7.8728e-04 ***
## factor(townid)12  11.503088   2.937798   3.915548 1.9356e-04 ***
## factor(townid)13   2.094158   0.899718   2.327572 2.2563e-02 *
## factor(townid)14  28.333414   3.061235   9.255551 3.8616e-14 ***
## factor(townid)15  51.395081   3.061235  16.789003  < 2.2e-16 ***
## factor(townid)16  27.391861   2.649377  10.338982 3.2750e-16 ***
## factor(townid)17  17.095081   3.061235   5.584374 3.3818e-07 ***
## factor(townid)18  -6.965968   1.646119  -4.231752 6.3400e-05 ***
## factor(townid)19   7.767081   3.061235   2.537238 1.3195e-02 *
## factor(townid)20   0.784311   1.491408   0.525887 6.0048e-01
## factor(townid)21  -2.573898   2.710245  -0.949692 3.4524e-01
## factor(townid)22  52.736461   1.298476  40.614107  < 2.2e-16 ***
## factor(townid)23  20.839525   3.061235   6.807555 1.9193e-09 ***
```

```
## factor(townid)24  11.285175   2.674577   4.219424 6.6278e-05 ***
## factor(townid)25   8.884501   3.061235   2.902261 4.8295e-03 **
## factor(townid)26  12.685337   3.061235   4.143863 8.6874e-05 ***
## factor(townid)27  10.168146   1.040668   9.770788 3.9625e-15 ***
## factor(townid)28 -13.177579   3.740138  -3.523287 7.2058e-04 ***
## factor(townid)29  16.988721   2.948856   5.761123 1.6339e-07 ***
## factor(townid)30  50.680910   1.243082  40.770365  < 2.2e-16 ***
## factor(townid)31   6.697963   0.738153   9.073955 8.6374e-14 ***
## factor(townid)32  16.444535   0.959845  17.132486  < 2.2e-16 ***
## factor(townid)33   4.278046   2.236386   1.912928 5.9475e-02 .
## factor(townid)34  20.326933   3.061235   6.640109 3.9592e-09 ***
## factor(townid)35  -0.206772   4.986850  -0.041463 9.6703e-01
## factor(townid)36  -5.617295   4.311429  -1.302885 1.9650e-01
## factor(townid)37  15.168414   3.061235   4.954999 4.1893e-06 ***
## factor(townid)38   4.011712   4.400296   0.911691 3.6478e-01
## factor(townid)39  -5.337609   0.878871  -6.073259 4.4390e-08 ***
## factor(townid)40   9.028549   6.715738   1.344387 1.8277e-01
## factor(townid)41   9.802649   0.179865  54.499981  < 2.2e-16 ***
## factor(townid)42   4.073540   0.421786   9.657826 6.5204e-15 ***
## factor(townid)43   7.707598   3.061235   2.517807 1.3885e-02 *
## factor(townid)44  10.199667   0.138106  73.853794  < 2.2e-16 ***
## factor(townid)45  12.291209   2.450222   5.016365 3.2962e-06 ***
## factor(townid)46  -1.846935   2.254780  -0.819120 4.1525e-01
## factor(townid)47   6.074427   2.373745   2.559006 1.2458e-02 *
## factor(townid)48  18.850537   1.820465  10.354789 3.0565e-16 ***
## factor(townid)49  14.266414   3.061235   4.660346 1.2997e-05 ***
## factor(townid)50   1.518698   1.341348   1.132218 2.6106e-01
## factor(townid)51   5.136051   2.442928   2.102416 3.8785e-02 *
## factor(townid)52   7.957253   2.190123   3.633245 5.0264e-04 ***
## factor(townid)53   1.653083   2.707382   0.610584 5.4327e-01
## factor(townid)54  17.629895   3.183129   5.538543 4.0783e-07 ***
## factor(townid)55   7.447431   3.061235   2.432819 1.7302e-02 *
## factor(townid)56   0.387900   1.907328   0.203373 8.3938e-01
## factor(townid)57  19.280553   2.357645   8.177888 4.6201e-12 ***
## factor(townid)58  -0.506143   2.567487  -0.197136 8.4424e-01
## factor(townid)59  35.639176   2.458157  14.498329  < 2.2e-16 ***
## factor(townid)60   3.969430   2.257132   1.758617 8.2616e-02 .
## factor(townid)61   8.865081   3.061235   2.895917 4.9183e-03 **
## factor(townid)62   0.790255   0.834253   0.947261 3.4647e-01
## factor(townid)63   3.130836   1.935490   1.617593 1.0984e-01
## factor(townid)64   9.304017   0.340686  27.309670  < 2.2e-16 ***
## factor(townid)65  17.484070   1.629367  10.730591  < 2.2e-16 ***
## factor(townid)66   7.597434   3.218428   2.360604 2.0777e-02 *
## factor(townid)67  24.830312   1.888584  13.147579  < 2.2e-16 ***
## factor(townid)68 -10.152494   3.362850  -3.019015 3.4384e-03 **
## factor(townid)69  20.400060   2.845721   7.168680 3.9780e-10 ***
## factor(townid)70  20.948414   3.061235   6.843126 1.6449e-09 ***
## factor(townid)71 -10.963482   3.552514  -3.086120 2.8175e-03 **
## factor(townid)72  12.420636   3.061235   4.057394 1.1802e-04 ***
## factor(townid)73  14.546291   0.261275  55.674311  < 2.2e-16 ***
## factor(townid)74  -1.768272   0.222186  -7.958507 1.2225e-11 ***
## factor(townid)75  -1.557151   3.880856  -0.401239 6.8936e-01
## factor(townid)76 -13.205519   3.750335  -3.521157 7.2558e-04 ***
## factor(townid)77   9.084072   2.844745   3.193281 2.0382e-03 **
```

```
## factor(townid)78  11.252859   3.061235   3.675921 4.3629e-04 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## RMSE: 44.3   Adj. R2: 0.180459
## F-test (1st stage), loan_amount: stat = 99.1    , p < 2.2e-16 , on 1 and 2,488 DoF.
##                       Wu-Hausman: stat =  6.90772, p = 0.008635, on 1 and 2,487 DoF.
```