Problem set 7

Education and Wages + Public Housing and Health

Jamie Pantazi Esmond

April 7, 2023

Table of contents

List of Figures

List of Tables

Task 1: Education, wages, and kids

Let's look once again at the effect of education on earnings. You'll use data from the 1976 Current Population Survey run by the US Census. The data is available as `wage` in the **wooldridge** R package—here I've just taken a subset of variables and renamed them. There are three columns:

Variable name	Description
`wage`	Average hourly earnings (in 1976 dollars)
`education`	Years of education
`n_kids`	Number of dependents living at home

You're interested in estimating β_1 in:

$$\text{Wage}_i = \beta_0 + \beta_1 \text{Education}_i + \epsilon_i$$

However, there is an issue with omitted variable bias and endogeneity. Instrumental variables can potentially help address the endogeneity.

Step 1

Load and look at the dataset

```
wages <- read_csv("data/wages.csv")
```

Step 2

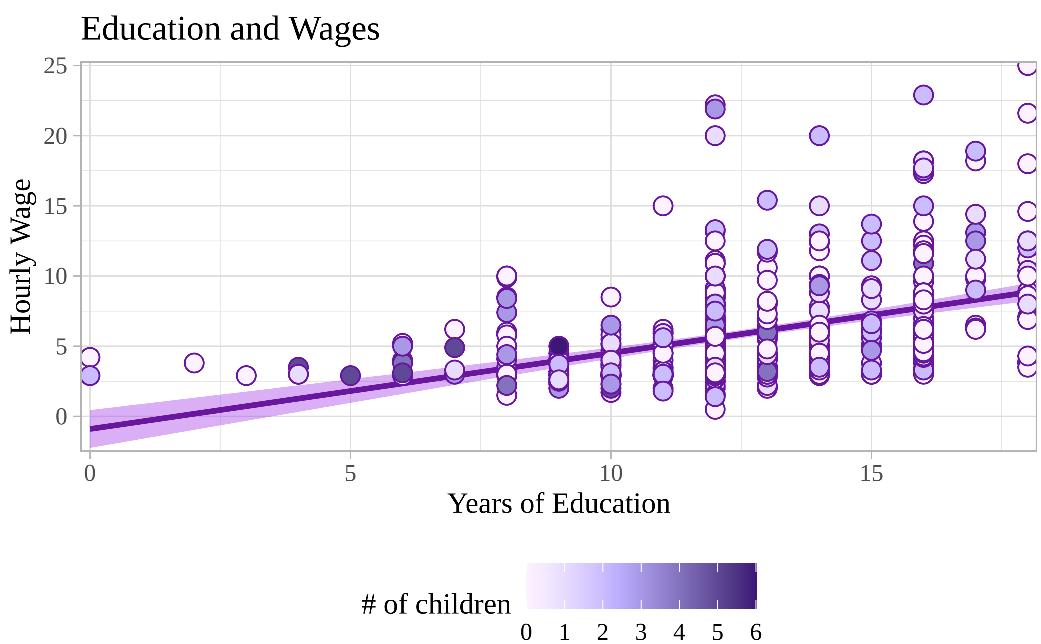
We need an instrument for education, since part of it is endogenous. *Do you think the variable `n_kids` (the number of children) would be a valid instrument? Does it meet the three requirements of a valid instrument?*

Relevance

```
wages %>%
  ggplot(aes(education, wage)) +
    geom_smooth(method = lm, color = "#68169E", fill = "#A338EA") +
    geom_point(aes(fill = n_kids), color = "#68169E", pch=21, size=3) +
```

```r
    scale_x_continuous(expand = expansion(mult = 0.01, add = 0)) +
    scale_y_continuous(expand = expansion(mult = 0.01, add = 0)) +
    scale_fill_continuous_sequential(palette = "Purples", l1 = 20, c2 = 70, p1 = 1,
                                     labels = label_number(accuracy = 1)) +
    labs(x = "Years of Education",
         y = "Hourly Wage",
         title = "Education and Wages",
         fill = "# of children") +
    theme_light() +
    theme(legend.position = "bottom",
          text = element_text(family = "serif"))
```

Figure 1: Education and Wages

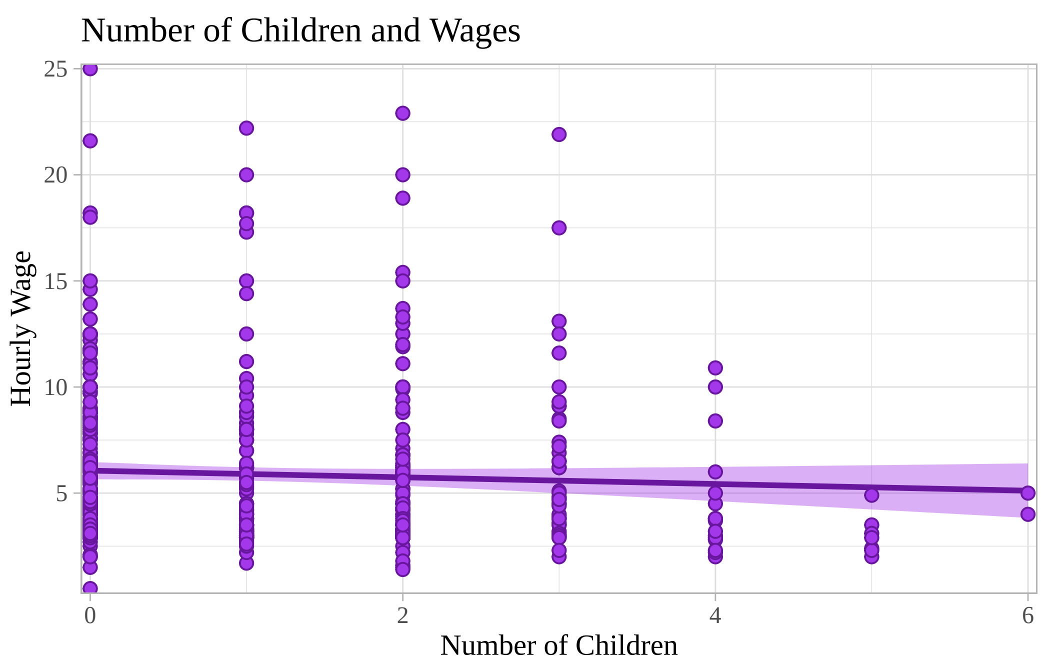


As seen in Figure 1, education *does* appear to be correlated with wage. The points have been colored to indicated the number of children.

Excudability

```
wages %>%
  ggplot(aes(n_kids, wage)) +
    geom_smooth(method = lm, color = "#68169E", fill = "#A338EA") +
    geom_point(color = "#68169E", fill = "#A338EA", pch=21, size=2) +
    scale_x_continuous(expand = expansion(mult = 0.01, add = 0)) +
    scale_y_continuous(expand = expansion(mult = 0.01, add = 0)) +
    labs(x = "Number of Children",
         y = "Hourly Wage",
         title = "Number of Children and Wages") +
    theme_light() +
    theme(legend.position = "bottom",
          text = element_text(family = "serif"))
```

Figure 2: Number of Children and Wages



However, according to Figure 2, the number of children is *not* correlated with wage.

Table 2: Education and Wages (Naive)

	Naive Model
(Intercept)	−0.902
	(0.685)
Years of Education	0.541***
	(0.053)
Num.Obs.	526
R2	0.164
RMSE	3.37

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Exogeneity

While we cannot test specifically for exogeneity, it does not seem likely that the number of children someone has would not be influenced both by wage and education, as well as many other factors.

```r
model <- lm(wage ~ education, data = wages)

modelsummary(list("Naive Model" = model),
             coef_rename = c(education = "Years of Education"),
             gof_omit = "IC|Log|Adj|p\\.value|statistic|se_type",
             stars = TRUE) %>%
  row_spec(c(1,3,5,7), background = "#8DE4FF")
```

Explain why it passes or fails each of the three requirements for a valid instrument. Test the requirements where possible using scatterplots and regression.

The only requirement that number of children passes to be a valid instrument is relevance, and that is only between education and wage. Number of children does not appear to have a positive influence on wages (if anything, the influence is negative). As far as exogeneity, there is no way to confirm, but it is not likely that the number of children is not influenced by many other factors.

Step 3

Assume that the number of children is a valid instrument (regardless of whatever you concluded earlier). Using the number of children (`n_kids`) as an instrument for education (`education`), estimate the effect of education on wages via two-stage least squares (2SLS) instrumental variables (IV).

Do this by hand: create a first stage model, extract the predicted education, and use predicted education in the second stage.

Interpret the coefficient that gives the effect of education on wages (β_1) and its significance.

```r
first_stage <- lm(education ~ n_kids, data = wages)

wages_predict <- augment_columns(first_stage, wages) %>%
  rename(educ_hat = .fitted)
head(wages_predict)
```

```
# A tibble: 6 x 10
   wage education n_kids educ_hat .se.fit .resid    .hat .sigma  .cooksd .std.~1
  <dbl>     <dbl>  <dbl>    <dbl>   <dbl>  <dbl>   <dbl>  <dbl>    <dbl>   <dbl>
1   3.1        11      2     12.1   0.148 -1.11  0.00299   2.71  2.54e-4  -0.411
2   3.2        12      3     11.6   0.218  0.361 0.00648   2.71  5.85e-5   0.134
3   3          11      2     12.1   0.148 -1.11  0.00299   2.71  2.54e-4  -0.411
4   6           8      0     13.1   0.153 -5.06  0.00320   2.70  5.63e-3  -1.87
5   5.3        12      1     12.6   0.118 -0.583 0.00190   2.71  4.44e-5  -0.216
6   8.8        16      0     13.1   0.153  2.94  0.00320   2.71  1.91e-3   1.09
# ... with abbreviated variable name 1: .std.resid
```

```r
second_stage <- lm(wage ~ educ_hat, data = wages_predict)
tidy(second_stage)
```

```
# A tibble: 2 x 5
  term        estimate std.error statistic p.value
  <chr>          <dbl>     <dbl>     <dbl>   <dbl>
1 (Intercept)    1.71      3.40      0.503   0.615
2 educ_hat       0.333     0.270     1.23    0.218
```

By calculating the expected wage according to how many children, we can use the expected value of education to determine how much of wage is caused by education. As the expected level of education increases, based on the number of children, the expected wage increases by 0.333. However, it is not statistically significant because the p value is .218, well above the .05 cutoff.

(Remember that you can also use the `iv_robust()` function from the **estimatr** package to run IV/2SLS models in one step with: `iv_robust(y ~ x | z, data = data)`, where `y` is the outcome, `x` is the policy/program, and `z` is the instrument. Try doing this to check your manual two-stage model.)

```r
model_2sls <- iv_robust(wage ~ education | n_kids, data = wages)
tidy(model_2sls)
```

```
         term  estimate std.error statistic   p.value   conf.low conf.high  df
1 (Intercept) 1.7093781 2.8030095 0.6098367 0.5422343 -3.7971383 7.2158945 524
2   education 0.3331669 0.2221214 1.4999318 0.1342343 -0.1031909 0.7695247 524
  outcome
1    wage
2    wage
```

Step 4

Run a naive model predicting the effect of education on wages (i.e. without any instruments).

How does this naive model compare with the IV model?

```r
tidy(model)
```

```
# A tibble: 2 x 5
  term        estimate std.error statistic  p.value
  <chr>          <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept)   -0.902    0.685      -1.32 1.89e- 1
2 education      0.541    0.0533     10.2  3.09e-22
```

The coefficient for the naive model is much higher and significant at 0.541. However the instrument model is no longer significant and decreased by 0.208, to 0.333.

Show the results side-by-side here:

```r
modelsummary(list("Naive (OLS)" = model,
                  "2SLS (manual)" = second_stage,
                  "2SLS (automatic)" = model_2sls),
             coef_rename = c(education = "Years of Education",
                             educ_hat = "Expected Years of Education"),
             gof_omit = "IC|Log|Adj|p\\.value|statistic|se_type",
             stars = TRUE) %>%
```

Table 3: Education and Wages (All Models)

	Naive (OLS)	2SLS (manual)	2SLS (automatic)
(Intercept)	−0.902	1.709	1.709
	(0.685)	(3.400)	(2.803)
Years of Education	0.541***		0.333
	(0.053)		(0.222)
Expected Years of Education		0.333	
		(0.270)	
Num.Obs.	526	526	526
R2	0.164	0.003	0.140
RMSE	3.37	3.69	3.42

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

```
    row_spec(c(3, 5), background = "#F5ABEA") %>%
    row_spec(c(1, 7, 9), background = "#F9E6EE")
```

Step 6

Explain which estimates (OLS vs. IV/2SLS) you would trust more (or why you distrust both).

The IV/2SLS models are more trustworthy than the OLS model because it is less significant and less substantial. Since the logic that more children would increase wages only through education makes no sense, it would be surprising to find a significant correlation. Having more children is most certainly influenced by many factors that also influence education and wages. Education and wages themselves influence the number of children someone might have.

The OLS model is even less trustworthy because it does not take into account any other factors at all. While it may be true that higher education causes higher wages, this model is insufficient to confirm that. Education can be influenced by a number of factors which also influence wages. Neither of these estimates are trustworthy.

Task 2: Public housing and health

Economic research shows that there is a potential (albeit weak) connection between health outcomes and residency in public housing. You are interested in finding the effect of public housing assistance on health outcomes. In the absence of experimental data, you must use observational data collected by the Georgia Department of Public Health. You have access to a dataset of 1,000 rows with the following columns:

Variable name	Description
`HealthStatus`	Health status on a scale from 1 = poor to 20 = excellent
`HealthBehavior`	Omitted variable (you can't actually measure this!)
`PublicHousing`	Number of years spent in public housing
`Supply`	Number of available public housing units in the city per 100 eligible households
`ParentsHealthStatus`	Health status of parents on a scale from 1 = poor to 20 = excellent
`WaitingTime`	Average waiting time before obtaining public housing in the city (in months)
`Stamp`	Dollar amount of food stamps (SNAP) spent each month
`Age`	Age
`Race`	Race; 1 = White, 2 = Black, 3 = Hispanic, 4 = Other
`Education`	Education; 1 = Some high school, 2 = High school, 3 = Bachelor's, 4 = Master's
`MaritalStatus`	Marital status; 1 = Single, 2 = Married, 3 = Widow, 4 = Divorced

(This is simulated data, but it's based on analysis by Angela R. Fertig and David A. Reingold)

Your goal is to measure the effect of living in public housing (`PublicHousing`) on health (`HealthStatus`). There is omitted variable bias, though, since people who care more about their health might be more likely to self-select into public housing and report a better health status score. The magic variable `HealthBehavior` measures this omitted variable, and you can use it as reference to make sure you get the models right (this is the same as "ability" in the examples in class), but don't include it in any of your actual models, since it's not real.

This data includes four potential instruments:

- `Supply`: Number of available public housing units in the city per 100 eligible households
- `ParentsHealthStatus`: Health status of parents on a scale from 1 = poor to 5 = excellent
- `WaitingTime`: Average waiting time before obtaining public housing in the city (in months)
- `Stamp`: Dollar amount of food stamps (SNAP) spent each month

You have three tasks:

Evaluate

1. Evaluate the suitability of each of the four potential instruments.

```
# problem-set-7/problem-set-7/
housing <- read_csv("data/public_housing.csv")
```

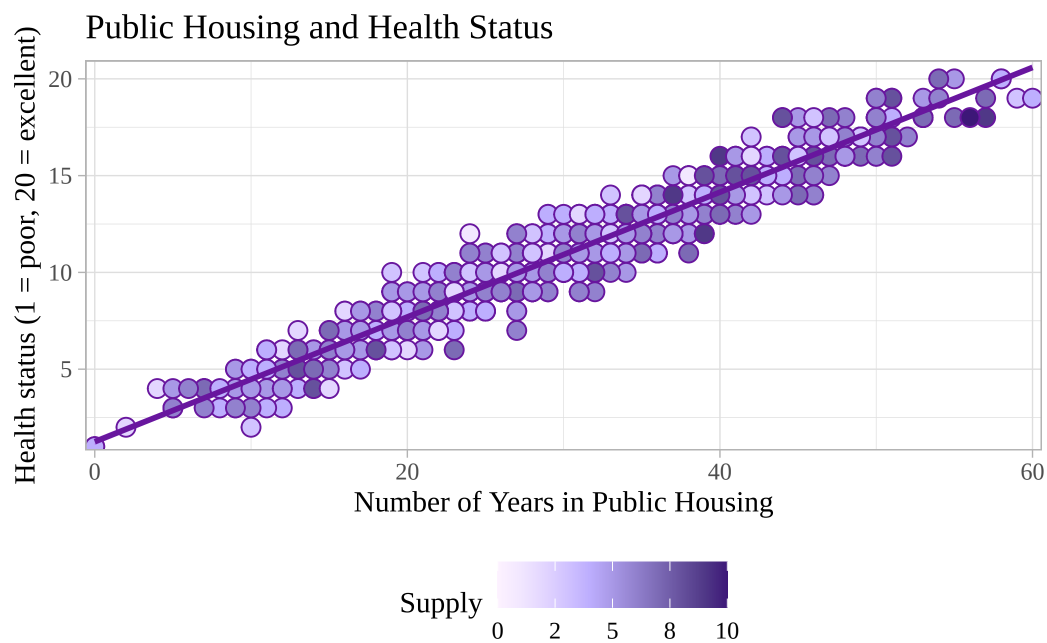
Supply

Relavance

Check if they (1) have *relevance* with a scatterplot and model and F-test,

```
housing %>%
  ggplot(aes(PublicHousing, HealthStatus)) +
    geom_point(aes(fill = Supply), color = "#68169E", pch=21, size=3) +
    geom_smooth(method = lm, color = "#68169E", fill = "#A338EA") +
    scale_x_continuous(expand = expansion(mult = 0.01, add = 0)) +
    scale_y_continuous(expand = expansion(mult = 0.01, add = 0)) +
    scale_fill_continuous_sequential(palette = "Purples", l1 = 20, c2 = 70, p1 = 1,
                                     labels = label_number(accuracy = 1)) +
    labs(x = "Number of Years in Public Housing",
         y = "Health status (1 = poor, 20 = excellent)",
         title = "Public Housing and Health Status",
         fill = "Supply") +
    theme_light() +
    theme(legend.position = "bottom",
          text = element_text(family = "serif"))
```

Figure 3: Public Housing and Health Status




```r
supply <- lm(HealthStatus ~ Supply, data = housing)
tidy(supply)
```

```
# A tibble: 2 x 5
  term        estimate std.error statistic   p.value
  <chr>          <dbl>     <dbl>     <dbl>     <dbl>
1 (Intercept)   10.2      0.357      28.6  5.22e-132
2 Supply         0.190    0.0676      2.81 5.01e-  3
```

```r
glance(supply)
```

```
# A tibble: 1 x 12
  r.squ~1 adj.r~2 sigma stati~3 p.value    df logLik   AIC   BIC devia~4 df.re~5
    <dbl>   <dbl> <dbl>   <dbl>   <dbl> <dbl>  <dbl> <dbl> <dbl>   <dbl>   <int>
1 0.00786 0.00687  3.45    7.91 0.00501     1 -2658. 5321. 5336.  11911.     998
# ... with 1 more variable: nobs <int>, and abbreviated variable names
#   1: r.squared, 2: adj.r.squared, 3: statistic, 4: deviance, 5: df.residual
```

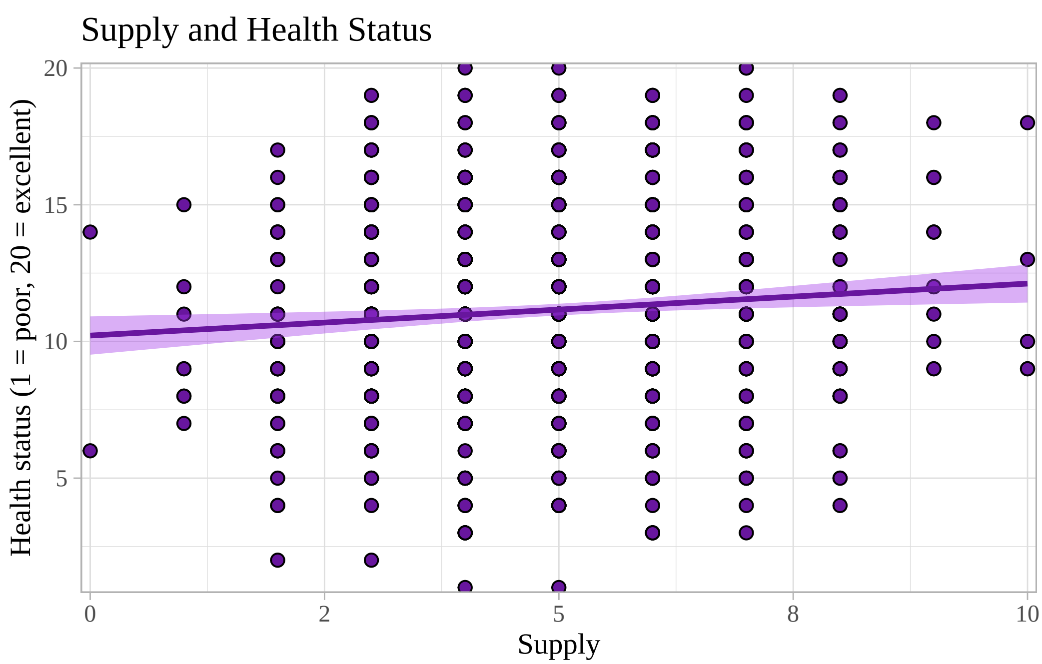
FAILED - Okay on relevance, but low f statistic.

Excudability

(2) meet the *excludability* assumption, and

```
housing %>%
  ggplot(aes(Supply, HealthStatus)) +
    geom_point(fill = "#68169E", pch=21, size=2) +
    geom_smooth(method = lm, color = "#68169E", fill = "#A338EA") +
    scale_x_continuous(expand = expansion(mult = 0.01, add = 0),
                       labels = label_number(accuracy = 1)) +
    scale_y_continuous(expand = expansion(mult = 0.01, add = 0)) +
    labs(x = "Supply",
         y = "Health status (1 = poor, 20 = excellent)",
         title = "Supply and Health Status") +
    theme_light() +
    theme(legend.position = "bottom",
          text = element_text(family = "serif"))
```

Figure 4: Supply and Health Status



FAILED - The slope is relatively flat so there may be other ways that supply influences health status.

Exogeneity

(3) meet the *exogeneity* assumption.

```
housing %>%
  ggplot(aes(HealthBehavior, Supply)) +
    geom_point(fill = "#68169E", pch=21, size=2) +
    geom_smooth(method = lm, color = "#68169E", fill = "#A338EA") +
    scale_x_continuous(expand = expansion(mult = 0.01, add = 0)) +
    scale_y_continuous(expand = expansion(mult = 0.01, add = 0),
                       labels = label_number(accuracy = 1)) +
    labs(x = "Health Behavior",
         y = "Supply",
         title = "Health Behavior and Supply") +
    theme_light() +
    theme(legend.position = "bottom",
          text = element_text(family = "serif"))
```

Figure 5: Health Behavior and Supply

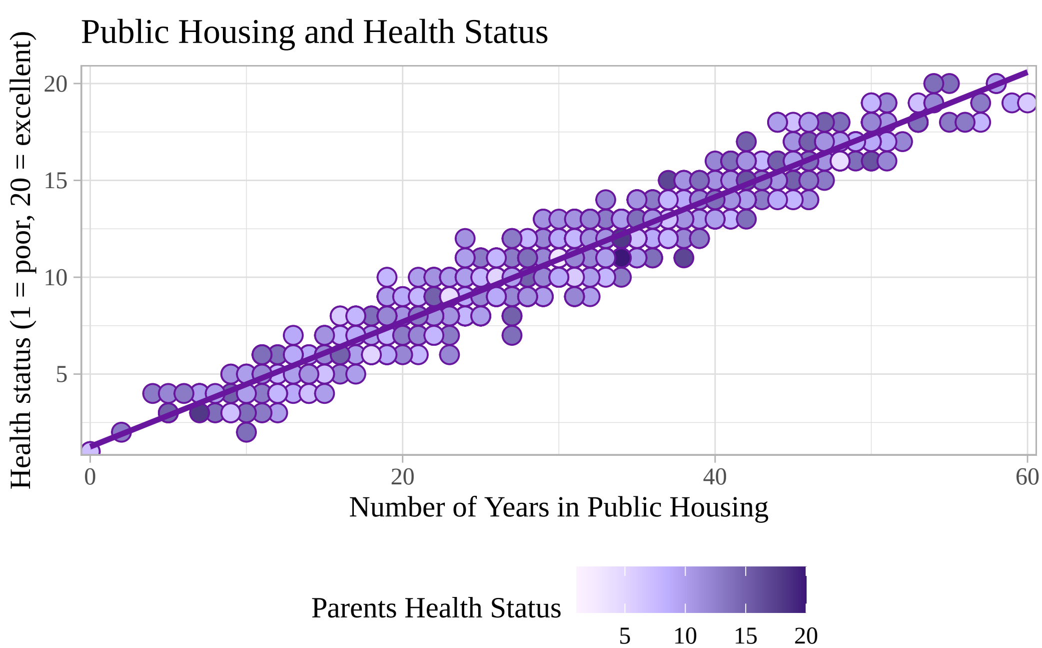
PASSED! - Health behavior is not correlated with supply.

Parents Health Status

Relavance

```r
housing %>%
  ggplot(aes(PublicHousing, HealthStatus)) +
    geom_point(aes(fill = ParentsHealthStatus), color = "#68169E", pch=21, size=3) +
    geom_smooth(method = lm, color = "#68169E", fill = "#A338EA") +
    scale_x_continuous(expand = expansion(mult = 0.01, add = 0)) +
    scale_y_continuous(expand = expansion(mult = 0.01, add = 0)) +
    scale_fill_continuous_sequential(palette = "Purples", l1 = 20, c2 = 70, p1 = 1) +
    labs(x = "Number of Years in Public Housing",
         y = "Health status (1 = poor, 20 = excellent)",
         title = "Public Housing and Health Status",
         fill = "Parents Health Status") +
    theme_light() +
    theme(legend.position = "bottom",
          text = element_text(family = "serif"))
```

Figure 6: Public Housing and Health Status



```r
parents <- lm(HealthStatus ~ ParentsHealthStatus, data = housing)
tidy(parents)
```

```
# A tibble: 2 x 5
  term                estimate std.error statistic  p.value
  <chr>                  <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept)          10.1       0.429      23.4  4.26e-97
2 ParentsHealthStatus   0.0995    0.0373      2.67 7.79e- 3
```

```r
glance(parents)
```

```
# A tibble: 1 x 12
  r.squ~1 adj.r~2 sigma stati~3 p.value    df logLik   AIC   BIC devia~4 df.re~5
    <dbl>   <dbl> <dbl>   <dbl>   <dbl> <dbl>  <dbl> <dbl> <dbl>   <dbl>   <int>
1 0.00707 0.00608  3.46    7.11 0.00779     1 -2658. 5322. 5337.  11921.     998
# ... with 1 more variable: nobs <int>, and abbreviated variable names
#   1: r.squared, 2: adj.r.squared, 3: statistic, 4: deviance, 5: df.residual
```

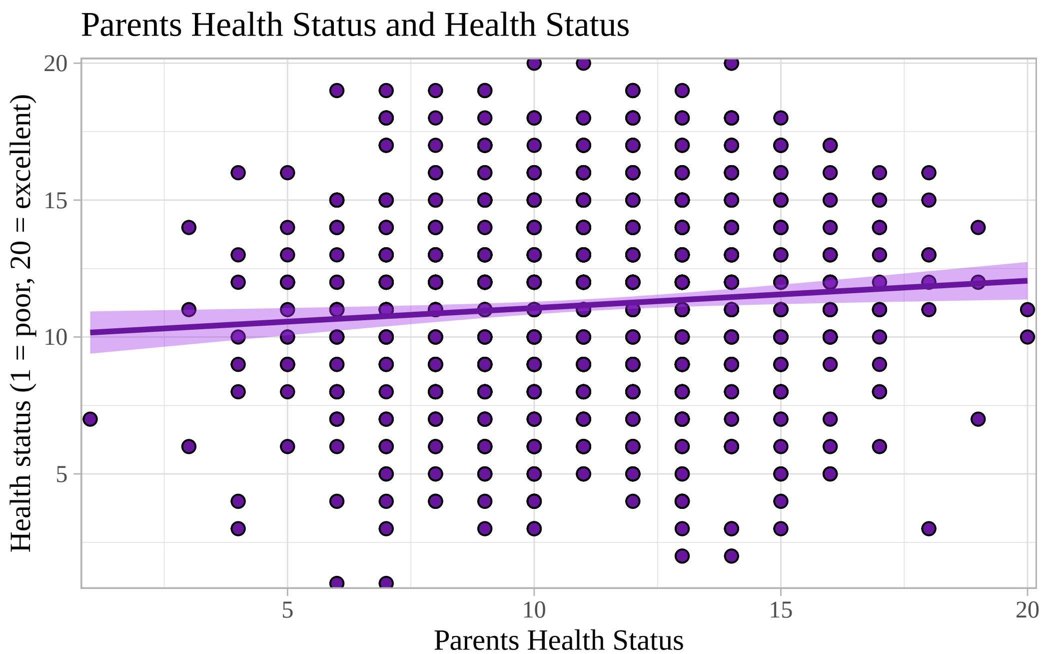
FAILED - Okay on relevance, but low f statistic.

Excudability

(2) meet the *excludability* assumption, and

```r
housing %>%
  ggplot(aes(ParentsHealthStatus, HealthStatus)) +
    geom_point(fill = "#68169E", pch=21, size=2) +
    geom_smooth(method = lm, color = "#68169E", fill = "#A338EA") +
    scale_x_continuous(expand = expansion(mult = 0.01, add = 0)) +
    scale_y_continuous(expand = expansion(mult = 0.01, add = 0)) +
    labs(x = "Parents Health Status",
         y = "Health status (1 = poor, 20 = excellent)",
         title = "Parents Health Status and Health Status") +
    theme_light() +
    theme(legend.position = "bottom",
          text = element_text(family = "serif"))
```

Figure 7: Parents Health Status and Health Status



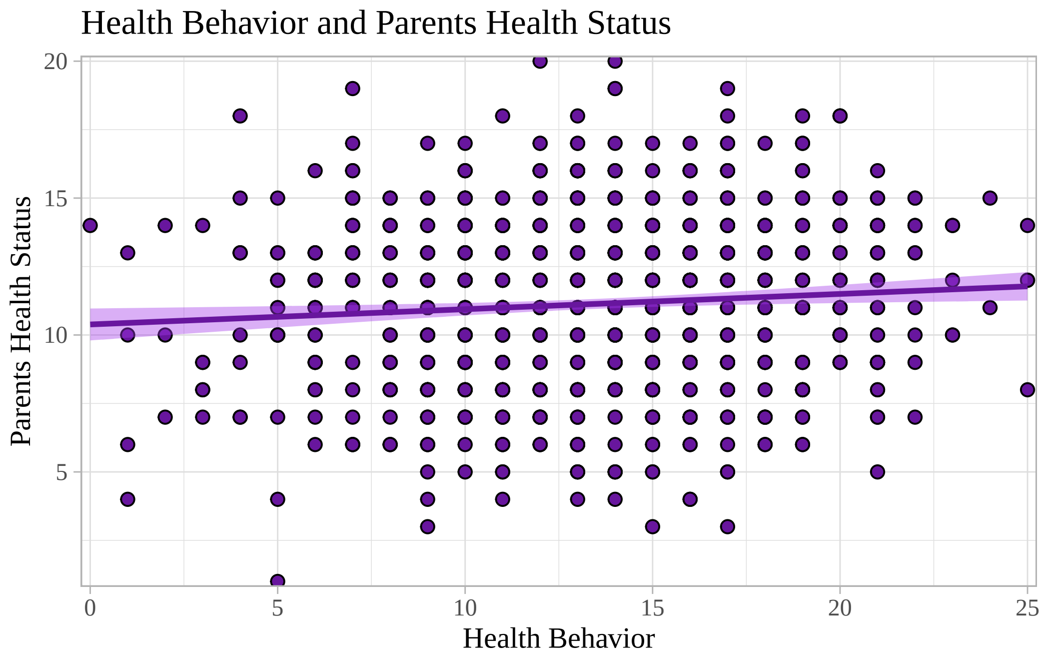
FAILED - The slope is relatively flat so there may be other ways that supply influences health status.

Exogeneity

(3) meet the *exogeneity* assumption.

```r
housing %>%
  ggplot(aes(HealthBehavior, ParentsHealthStatus)) +
    geom_point(fill = "#68169E", pch=21, size=2) +
    geom_smooth(method = lm, color = "#68169E", fill = "#A338EA") +
    scale_x_continuous(expand = expansion(mult = 0.01, add = 0)) +
    scale_y_continuous(expand = expansion(mult = 0.01, add = 0)) +
    labs(x = "Health Behavior",
         y = "Parents Health Status",
         title = "Health Behavior and Parents Health Status") +
    theme_light() +
    theme(legend.position = "bottom",
          text = element_text(family = "serif"))
```

Figure 8: Health Behavior and Parents Health Status



FAILED - Though it is not extreme, there is a bit of upward slope indicating a possible correlation between health behavior and parents health status.

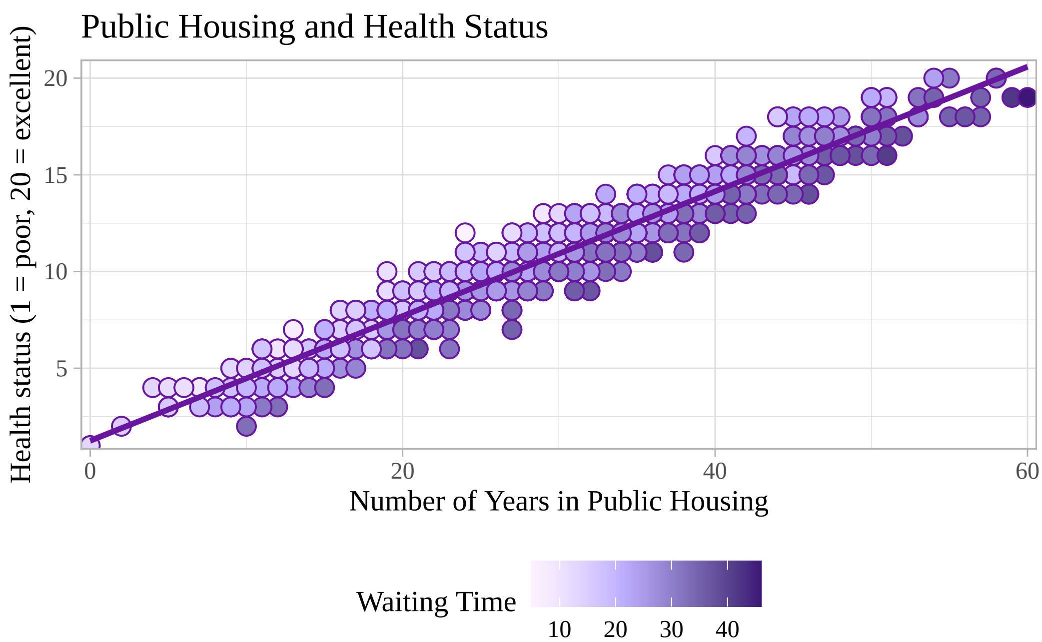
Waiting Time

Relavance

```
housing %>%
  ggplot(aes(PublicHousing, HealthStatus)) +
    geom_point(aes(fill = WaitingTime), color = "#68169E", pch=21, size=3) +
    geom_smooth(method = lm, color = "#68169E", fill = "#A338EA") +
    scale_x_continuous(expand = expansion(mult = 0.01, add = 0)) +
    scale_y_continuous(expand = expansion(mult = 0.01, add = 0)) +
    scale_fill_continuous_sequential(palette = "Purples", l1 = 20, c2 = 70, p1 = 1) +
    labs(x = "Number of Years in Public Housing",
         y = "Health status (1 = poor, 20 = excellent)",
         title = "Public Housing and Health Status",
         fill = "Waiting Time") +
    theme_light() +
```

```r
    theme(legend.position = "bottom",
          text = element_text(family = "serif"))
```

Figure 9: Public Housing and Health Status




```r
wait <- lm(HealthStatus ~ WaitingTime, data = housing)
tidy(wait)
```

```
# A tibble: 2 x 5
  term        estimate std.error statistic  p.value
  <chr>          <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept)    5.85     0.426       13.7 2.26e-39
2 WaitingTime    0.213    0.0165      12.9 3.55e-35
```

```r
glance(wait)
```

```
# A tibble: 1 x 12
  r.squared adj.r.squa~1 sigma stati~2  p.value    df logLik   AIC   BIC devia~3
      <dbl>        <dbl> <dbl>   <dbl>    <dbl> <dbl>  <dbl> <dbl> <dbl>   <dbl>
```

```
1     0.142        0.141  3.21    166. 3.55e-35     1 -2585. 5176. 5190.  10297.
# ... with 2 more variables: df.residual <int>, nobs <int>, and abbreviated
#   variable names 1: adj.r.squared, 2: statistic, 3: deviance
```

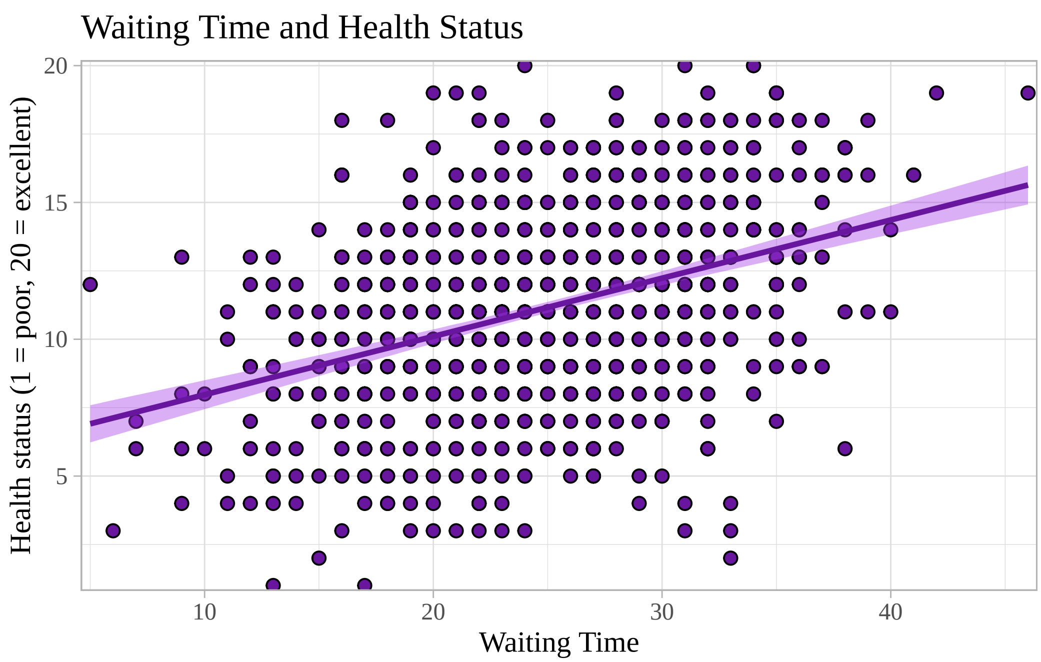
PASSED! - High relevance and high f statistic.

Excudability

(2) meet the *excludability* assumption, and

```r
housing %>%
  ggplot(aes(WaitingTime, HealthStatus)) +
    geom_point(fill = "#68169E", pch=21, size=2) +
    geom_smooth(method = lm, color = "#68169E", fill = "#A338EA") +
    scale_x_continuous(expand = expansion(mult = 0.01, add = 0)) +
    scale_y_continuous(expand = expansion(mult = 0.01, add = 0)) +
    labs(x = "Waiting Time",
         y = "Health status (1 = poor, 20 = excellent)",
         title = "Waiting Time and Health Status") +
    theme_light() +
    theme(legend.position = "bottom",
          text = element_text(family = "serif"))
```

Figure 10: Waiting Time and Health Status



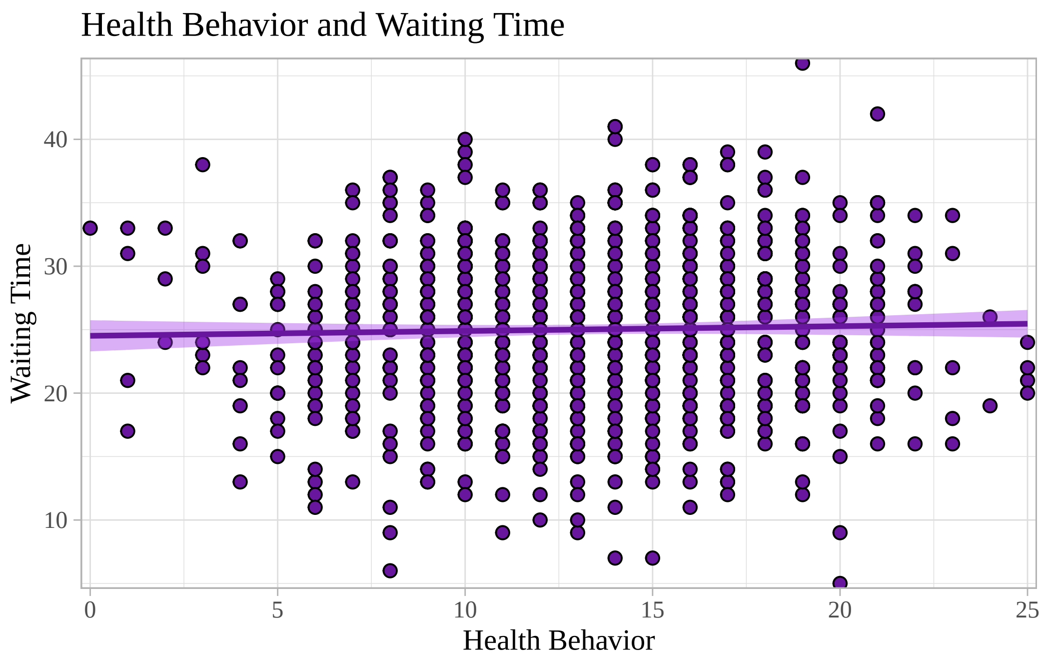
PASSED! - The slope is substantial in a positive direction. There is a significant correlation between waiting time and health status.

Exogeneity

(3) meet the *exogeneity* assumption.

```
housing %>%
  ggplot(aes(HealthBehavior, WaitingTime)) +
    geom_point(fill = "#68169E", pch=21, size=2) +
    geom_smooth(method = lm, color = "#68169E", fill = "#A338EA") +
    scale_x_continuous(expand = expansion(mult = 0.01, add = 0)) +
    scale_y_continuous(expand = expansion(mult = 0.01, add = 0)) +
    labs(x = "Health Behavior",
         y = "Waiting Time",
         title = "Health Behavior and Waiting Time") +
    theme_light() +
    theme(legend.position = "bottom",
          text = element_text(family = "serif"))
```

Figure 11: Health Behavior and Waiting Time



PASSED! - Health behavior is not correlated with waiting time.

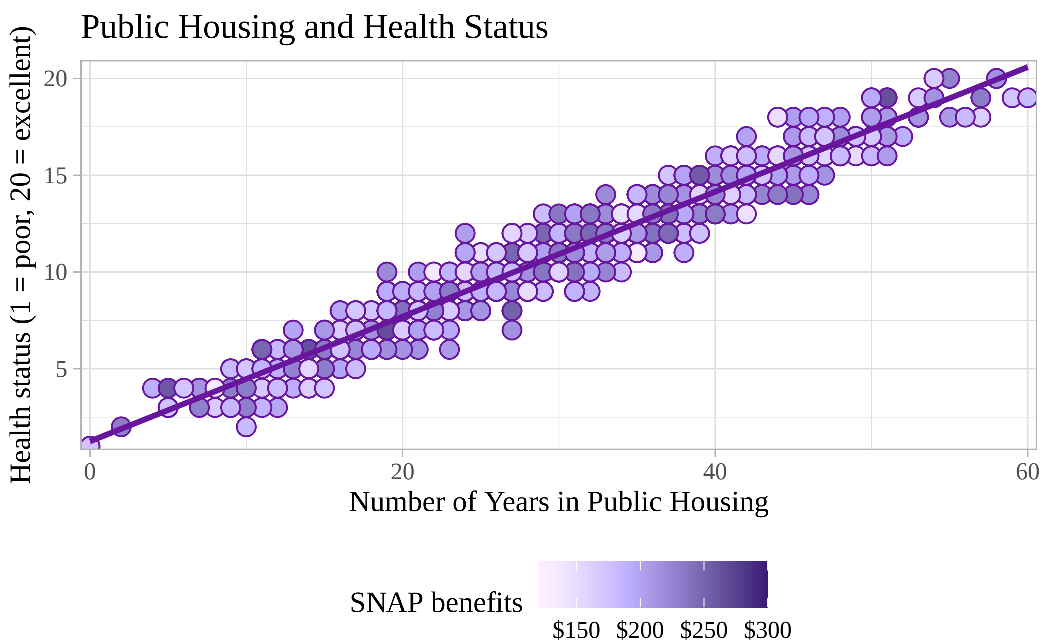
SNAP benefits

Relavance

```
housing %>%
  ggplot(aes(PublicHousing, HealthStatus)) +
    geom_point(aes(fill = Stamp), color = "#68169E", pch=21, size=3) +
    geom_smooth(method = lm, color = "#68169E", fill = "#A338EA") +
    scale_x_continuous(expand = expansion(mult = 0.01, add = 0)) +
    scale_y_continuous(expand = expansion(mult = 0.01, add = 0)) +
    scale_fill_continuous_sequential(palette = "Purples", l1 = 20, c2 = 70, p1 = 1,
                                     labels = dollar) +
    labs(x = "Number of Years in Public Housing",
         y = "Health status (1 = poor, 20 = excellent)",
         title = "Public Housing and Health Status",
         fill = "SNAP benefits") +
    theme_light() +
```

```
    theme(legend.position = "bottom",
          text = element_text(family = "serif"))
```

Figure 12: Public Housing and Health Status




```
SNAP <- lm(HealthStatus ~ Stamp, data = housing)
tidy(SNAP)
```

```
# A tibble: 2 x 5
  term        estimate std.error statistic  p.value
  <chr>          <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept) 11.5       0.795      14.4   4.67e-43
2 Stamp       -0.00157   0.00399    -0.393 6.95e- 1
```

```
glance(SNAP)
```

```
# A tibble: 1 x 12
  r.squared adj.r.squared sigma stati~1 p.value    df logLik   AIC   BIC devia~2
      <dbl>         <dbl> <dbl>   <dbl>   <dbl> <dbl>  <dbl> <dbl> <dbl>   <dbl>
```

```
1  0.000154     -0.000847  3.47   0.154   0.695     1 -2662. 5329. 5344.  12004.
# ... with 2 more variables: df.residual <int>, nobs <int>, and abbreviated
#   variable names 1: statistic, 2: deviance
```

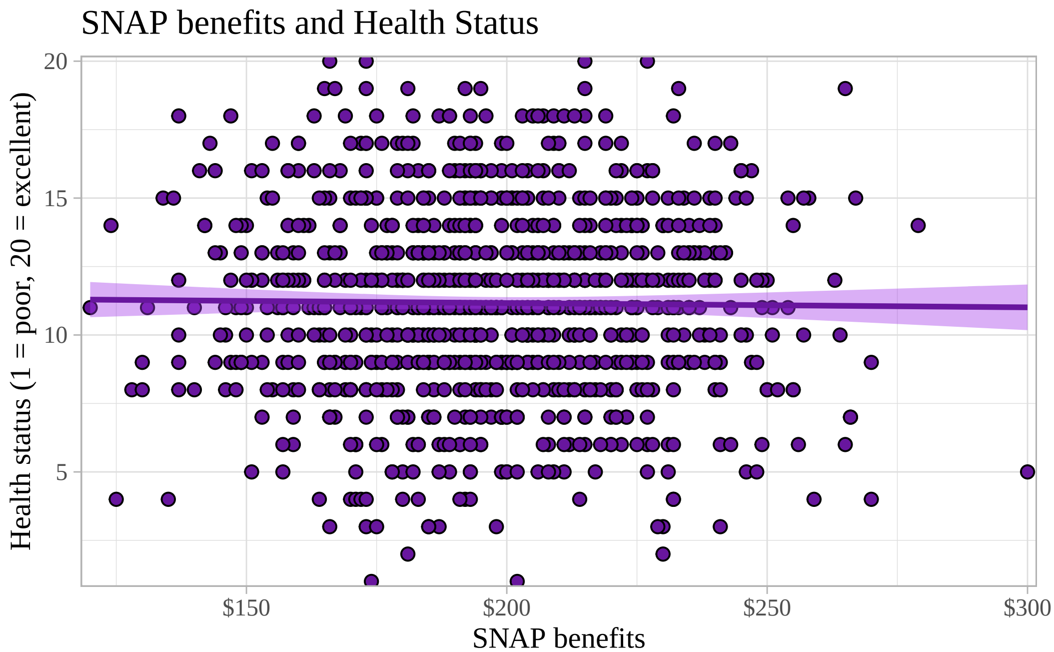
FAILED - Low relevance and very low f statistic.

Excudability

(2) meet the *excludability* assumption, and

```
housing %>%
  ggplot(aes(Stamp, HealthStatus)) +
    geom_point(fill = "#68169E", pch=21, size=2) +
    geom_smooth(method = lm, color = "#68169E", fill = "#A338EA") +
    scale_x_continuous(expand = expansion(mult = 0.01, add = 0),
                       labels = dollar) +
    scale_y_continuous(expand = expansion(mult = 0.01, add = 0)) +
    labs(x = "SNAP benefits",
         y = "Health status (1 = poor, 20 = excellent)",
         title = "SNAP benefits and Health Status") +
    theme_light() +
    theme(legend.position = "bottom",
          text = element_text(family = "serif"))
```

Figure 13: SNAP benefits and Health Status



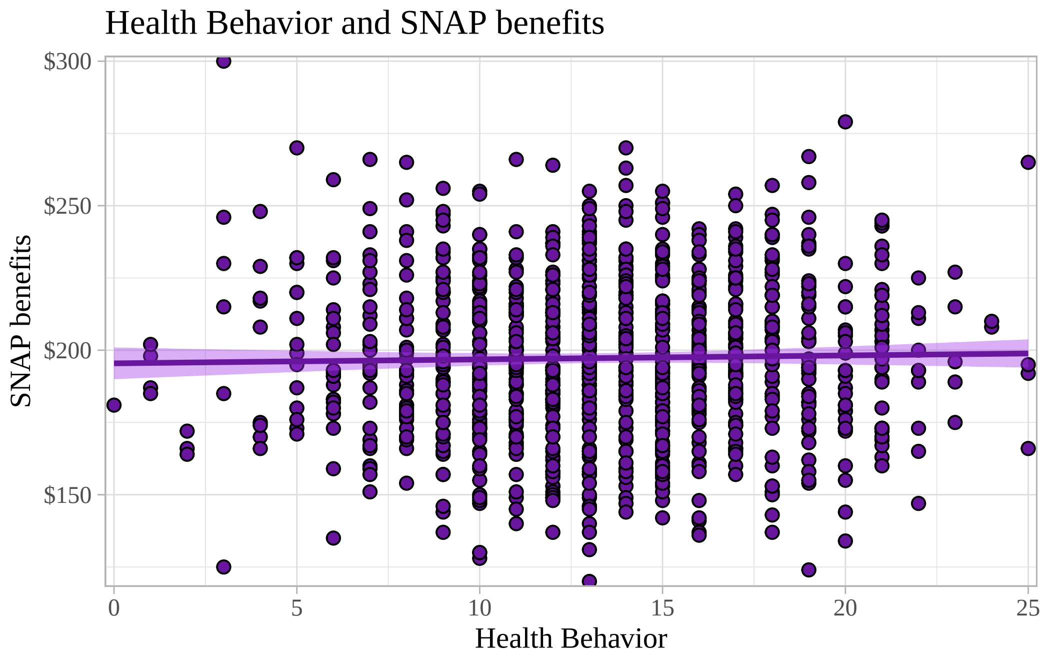
FAILED - The slope is almost completely flat so there may be other ways that supply influences health status.

Exogeneity

(3) meet the *exogeneity* assumption.

```r
housing %>%
  ggplot(aes(HealthBehavior, Stamp)) +
    geom_point(fill = "#68169E", pch=21, size=2) +
    geom_smooth(method = lm, color = "#68169E", fill = "#A338EA") +
    scale_x_continuous(expand = expansion(mult = 0.01, add = 0)) +
    scale_y_continuous(expand = expansion(mult = 0.01, add = 0),
                       labels = dollar) +
    labs(x = "Health Behavior",
         y = "SNAP benefits",
         title = "Health Behavior and SNAP benefits") +
    theme_light() +
    theme(legend.position = "bottom",
          text = element_text(family = "serif"))
```

Figure 14: Health Behavior and SNAP benefits



PASSED! - Health behavior is not correlated with SNAP benefits.

Choose one of these as your main instrument and justify why it's the best. Explain why the other three are not.

Instrument	Relevance	Excudability	Exogeneity
`Supply`	FAIL	FAIL	PASS
`ParentsHealthStatus`	FAIL	FAIL	FAIL
`WaitingTime`	**PASS**	**PASS**	**PASS**
`Stamp`	FAIL	FAIL	PASS

The obvious choice here for an instrument would be waiting time. It is the only variable that fulfills all three requirements. None of the other three variables even pass the relevance and excudability tests, let alone exogeneity which would not actually be testable in a real world situation.

Naive Model

2. Estimate a naive model of the effect of public housing on health status (i.e. without any instruments). You can include any control variables you feel appropriate (i.e. that fit in your

Table 6: Public Housing and Health Outcomes (Naive)

	Naive Model	Naive + Controls
(Intercept)	1.254***	−1.197***
	(0.088)	(0.226)
Years in Public Housing	0.322***	0.321***
	(0.003)	(0.003)
Num.Obs.	1000	1000
R2	0.933	0.943
RMSE	0.89	0.82

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

causal model). If you use variables that are categorical like race, education, or marital status, make sure you wrap them with `as.factor()` to treat them as categories instead of numbers (e.g. `as.factor(education)`).

```r
modelh <- lm(HealthStatus ~ PublicHousing, data = housing)

modelh2 <- lm(HealthStatus ~ PublicHousing +
              Age + as.factor(Race) + as.factor(Education) + as.factor(MaritalStatus),
            data = housing)

modelsummary(list("Naive Model" = modelh,
                  "Naive + Controls" = modelh2),
             coef_omit = c(-1, -2),
             coef_rename = c(PublicHousing = "Years in Public Housing"),
             gof_omit = "IC|Log|Adj|p\\.value|statistic|se_type",
             stars = TRUE) %>%
  row_spec(c(1,3,5,7), background = "#8DE4FF")
```

2SLS IV Model

3. Estimate the effect of public housing on health status using 2SLS IV. You can use `iv_robust()` to do it all in one step if you want (but you'll still need to run a first-stage model to find the F statistic). Compare the results with the naive model.

```r
first_stage2 <- lm(PublicHousing ~ WaitingTime, data = housing)

health_predict <- augment_columns(first_stage2, housing) %>%
```

```r
  rename(public_hat = .fitted) %>%
  select(PublicHousing, WaitingTime, public_hat, HealthStatus)
head(health_predict)
```

```
# A tibble: 6 x 4
  PublicHousing WaitingTime public_hat HealthStatus
          <dbl>       <dbl>      <dbl>        <dbl>
1            22          19       25.1           10
2            32          34       39.3           11
3            31          35       40.3           10
4            33          18       24.1           13
5            38          35       40.3           12
6            30          17       23.2           12
```

```r
second_stage2 <- lm(HealthStatus ~ public_hat, data = health_predict)
tidy(second_stage2)
```

```
# A tibble: 2 x 5
  term        estimate std.error statistic  p.value
  <chr>          <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept)    4.28     0.545       7.85 1.04e-14
2 public_hat     0.224    0.0174     12.9  3.55e-35
```

```r
model_2sls2 <- iv_robust(HealthStatus ~ PublicHousing | WaitingTime,
                         data = housing)
tidy(model_2sls2)
```

```
           term  estimate   std.error statistic       p.value  conf.low
1   (Intercept) 4.2804039 0.235296328  18.19155  4.375792e-64 3.8186716
2 PublicHousing 0.2239024 0.007555483  29.63442 5.842195e-139 0.2090759
  conf.high  df      outcome
1 4.7421362 998 HealthStatus
2 0.2387288 998 HealthStatus
```

```r
forbidden <- lm(HealthStatus ~ PublicHousing + HealthBehavior,
                data = housing)

model_2sls_supply <- iv_robust(HealthStatus ~ PublicHousing | Supply,
```

Table 7: Public Housing and Health Outcomes (All Instruments)

	Waiting Time	Supply	Parents Health	SNAP benefits	Forbidden
(Intercept)	4.280***	3.152***	−0.179	1.936	0.555***
	(0.235)	(0.929)	(1.217)	(6.258)	(0.064)
Years in Public Housing	0.224***	0.261***	0.369***	0.300	0.229***
	(0.008)	(0.030)	(0.040)	(0.203)	(0.003)
HealthBehavior					0.268***
					(0.008)
Num.Obs.	1000	1000	1000	1000	1000
R2	0.847	0.899	0.914	0.929	0.969
RMSE	1.36	1.10	1.02	0.92	0.61

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

```r
                               data = housing)

model_2sls_parents <- iv_robust(HealthStatus ~ PublicHousing | ParentsHealthStatus,
                               data = housing)

model_2sls_SNAP <- iv_robust(HealthStatus ~ PublicHousing | Stamp,
                               data = housing)

modelsummary(list("Waiting Time" = model_2sls2,
                  "Supply" = model_2sls_supply,
                  "Parents Health" = model_2sls_parents,
                  "SNAP benefits" = model_2sls_SNAP,
                  "Forbidden" = forbidden),
             coef_rename = c(PublicHousing = "Years in Public Housing"),
             gof_omit = "IC|Log|Adj|p\\.value|statistic|se_type",
             stars = TRUE) %>%
  row_spec(c(3), background = "#F5ABEA") %>%
  row_spec(c(1, 5, 7), background = "#F9E6EE") %>%
  column_spec(2:6, width = "4em")
```

Table 8: Public Housing and Health Outcomes (Waiting Time as an Instrumental Variable)

	Naive (OLS)	Naive + Controls (OLS)	2SLS (manual)	2SLS (automatic)	Forbidden
(Intercept)	1.254***	−1.197***	4.280***	4.280***	0.555***
	(0.088)	(0.226)	(0.545)	(0.235)	(0.064)
Years in Public Housing	0.322***	0.321***		0.224***	0.229***
	(0.003)	(0.003)		(0.008)	(0.003)
Expected Years in Public Housing			0.224***		
			(0.017)		
HealthBehavior					0.268***
					(0.008)
Num.Obs.	1000	1000	1000	1000	1000
R2	0.933	0.943	0.142	0.847	0.969
RMSE	0.89	0.82	3.21	1.36	0.61

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All Models

```r
modelsummary(list("Naive (OLS)" = modelh,
                  "Naive + Controls (OLS)" = modelh2,
                  "2SLS (manual)" = second_stage2,
                  "2SLS (automatic)" = model_2sls2,
                  "Forbidden" = forbidden),
             coef_omit = c(-1, -2, -13, -14),
             coef_rename = c(PublicHousing = "Years in Public Housing",
                             public_hat = "Expected Years in Public Housing"),
             gof_omit = "IC|Log|Adj|p\\.value|statistic|se_type",
             stars = TRUE) %>%
  row_spec(c(3, 5), background = "#F5ABEA") %>%
  row_spec(c(1, 7, 9, 11), background = "#F9E6EE") %>%
  column_spec(1, width = "8em") %>%
  column_spec(2:6, width = "5em")
```

Which model do you trust (if any), and why?

While the naive model is significant, even when controlling for other factors, there are still unobserved variables that could be influencing health and housing. By using waiting time

as an instrument, we assume that wait time for a public housing unit influences health outcomes only through housing. We can assume that wait time does not influence health behavior because people waiting for public housing are not fundamentally different from people already in public housing in regard to their health behavior. If our assumptions are correct, if follows logically, that the direct impact of public housing on health outcomes is significant and positive. For each additional year in public housing, using wait time as an instrument, health status is expected to increase 0.224. Though these are assumptions we would usually not be able to prove, the forbidden model shows that the "actual" causal effect of public housing on health outcomes is 0.229. This is only a 0.005 difference.