Case 2: Racial Discrimination and the Fair Housing Act

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How to use this case

- Code will be marked using the monospaced Courier New font. For example, we will run regressions with the `lm` function.
- I will elaborate on some points using footnotes. These footnotes are explicitly not testable material. They might help your understanding or provide some interesting facts.

Introduction

This case centers around data from housing audits, which measured racial discrimination in the behavior of realtors (see (Yinger 1986) for more information). Realtors were a population of interest because they, over time, shape the very neighborhoods we live in. Some conflate racial problems with local neighborhood effects (i.e., arguing schools may be underfunded, but that is because of the local tax base, rather than racial bias), one should realize that the sorting of different racial groups into different neighborhoods was a policy, sometimes reinforced by the real estate industry.[1]

We will be looking at evidence of this discrimination from a housing audit, conducted in 1981. In this study, black and white auditors were sent to different realtors to make inquiries about apartments. Some of the key measures of interest were

- Whether the realtor said the advertised unit was available
- Whether the auditor was invited to inspect the unit
- Whether the auditor received a callback from the realtor

We'll be using this case as an example of the correct interpretation of linear regression and interaction effects. As always, we should first load an inspect the data[2].

Load and explore the data

The variables representing the following:

- `unitAvail` Binary. Whether the advertised unit was available.
- `unitInspec` Binary. Whether the advertised unit was inspected.
- `askIncome` Binary. Whether the auditor was asked about their income.
- `callBack` Binary. Whether the auditor was asked to call back.

[1] This is case is only a small part of a *much* larger conversation, and I am not an expert in this subject.
[2] This is a dataset I cleaned. For the original datasets visit https://joyinger.expressions.syr.edu/data-sets/

- `finHelp` Binary. Whether the auditor was offered financial help.
- `followUp` Binary. Whether the agent followed up with the auditor.
- `otherInspec` Binary. Whether other units were inspected.
- `agentAge` Numeric. The age of the agent.
- `auditorChild` Binary. Whether the auditor had children.
- `auditorKid` Binary. Whether the auditor had young children.
- `auditorCouple` Binary. Whether the auditor was part of a couple.
- `isQualified` Binary. Whether the auditor was deemed as qualified to rent the unit.
- `agentBLK` Binary. Whether the agent was black.
- `agentFEM` Binary. Whether the agent was female.
- `auditID` Numeric. A unique identifier for each audit.
- `pctBLK` Numeric. What percent of the neighborhood is black.
- `houseVAL` Numeric. The value of the house, in dollar.
- `officeBLK` Numeric. The percentage of the neighborhood the realtor is located in is black.
- `inCity` Binary. Whether the realtor is located in the city.
- `sameAgent` Binary. Whether both teammates saw the same agent.
- `race` Text. The race of the auditor.

Below we use R to load the data and view basic summary statistics.

```r
setwd('C:/Users/Avery Haviv/Dropbox/Teaching Lectures/Housing Case')
housingData = read.csv('HousingData.csv')
summary(housingData)
```

```
##    unitAvail        unitInspec       askIncome         callBack
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.:1.0000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :1.0000   Median :1.0000   Median :0.0000   Median :0.0000
##  Mean   :0.8382   Mean   :0.5694   Mean   :0.2488   Mean   :0.4644
##  3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:0.0000   3rd Qu.:1.0000
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.0000   Max.   :1.0000
##  NA's   :5
##     finHelp          followUp       otherInspec         agentAge
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :20.00
##  1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:0.0000   1st Qu.:35.00
##  Median :0.0000   Median :0.0000   Median :0.0000   Median :40.00
##  Mean   :0.3196   Mean   :0.1998   Mean   :0.2997   Mean   :42.37
##  3rd Qu.:1.0000   3rd Qu.:0.0000   3rd Qu.:1.0000   3rd Qu.:50.00
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.0000   Max.   :74.00
##
##   auditorChild      auditorKid     auditorCouple     isQualified
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :0.000
##  1st Qu.:0.6346   1st Qu.:0.0000   1st Qu.:1.0000   1st Qu.:0.000
##  Median :1.0000   Median :0.0000   Median :1.0000   Median :0.000
##  Mean   :0.7421   Mean   :0.2634   Mean   :0.8787   Mean   :0.216
##  3rd Qu.:1.0000   3rd Qu.:0.3654   3rd Qu.:1.0000   3rd Qu.:0.000
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.0000   Max.   :1.000
```

```
##
##     agentBLK          agentFEM          auditID              pctBLK
##  Min.   :0.00000   Min.   :0.0000   Min.   : 52001008   Min.   : 0.000
##  1st Qu.:0.00000   1st Qu.:0.0000   1st Qu.:160019424   1st Qu.: 1.260
##  Median :0.00000   Median :1.0000   Median :404000064   Median : 4.400
##  Mean   :0.02202   Mean   :0.6254   Mean   :351892637   Mean   : 7.440
##  3rd Qu.:0.00000   3rd Qu.:1.0000   3rd Qu.:556058688   3rd Qu.: 7.661
##  Max.   :1.00000   Max.   :1.0000   Max.   :884096128   Max.   :94.590
##
##     houseVAL        officeBLK          inCity          sameAgent
##  Min.   : 11500   Min.   : 0.000   Min.   :0.0000   Min.   :0.0000
##  1st Qu.: 75000   1st Qu.: 0.680   1st Qu.:0.0000   1st Qu.:0.0000
##  Median :105000   Median : 2.010   Median :0.0000   Median :1.0000
##  Mean   :128422   Mean   : 5.924   Mean   :0.2479   Mean   :0.5856
##  3rd Qu.:161250   3rd Qu.: 5.720   3rd Qu.:0.5750   3rd Qu.:1.0000
##  Max.   :377500   Max.   :94.490   Max.   :1.0000   Max.   :2.0000
##
##        race
##  minority:1081
##  white   :1081
##
##
##
##
##
```

A few things I noted when looking at these statistics:

- Several of the binary variables have very low incidence rates (i.e., `agentBLK`, `pctBLK`). Analysis using these varaibles will have large standard errors, as we don't have a lot of data in these cases.
- The race variable is balanced, as expected given the study design.
- The `sameAgent` variable is supposed to be binary, but for some reason it takes on the value '2'. I'd follow up with the data source about this to see if there was a coding error, or something I didn't understand. In the interim, I will compare values of '0' versus '>0'.

There are a number of factors that affect how a realtor would treat an applicant. What's interesting about this study is that it makes use of three different techniques to account for such factors.

1. **Randomize.** As discussed in Topic 1, randomization is the very best way to account for missing factors. However, it is not always possible to randomly assign characteristics. For example, while one can randomly assign the race of a name appearing on a resume (as in our previous case), one cannot randomize the race of an auditor who shows up in person! In this case, the designers of the study were worried about *order effects*, wherein the order in which the auditors were seen affects the outcome. So, they randomized the order in which the auditors visited the realtor. This ensures that order is not correlated with race, and therefore will not cause bias, even if omitted.
2. **Match.** Factors that couldn't be randomized were matched. This means that auditors were paired according to their family characteristics, economic characteristics, and where possible their personalities. Because these characteristics were equal between black and white auditors, they are not correlated with race, and therefore their omission will not cause bias.
3. **Control.** Finally, for characteristics that cannot be randomized or matched, one can simply control for these factors in the regression. This could include variables like time of year, or characteristics that could not be precisely matched.

In experimental design, the above order ranks our preference in accounting for other factors: randomize and match everything you can, control for the rest.

Analysis

Given the study design, we can run a straight unbiased univariate regression. Note that this is only a feature of experimental contexts, and only because of the care the study authors used. We will see how race affects whether the realtor said the unit was available, whether the unit was inspected, and whether the auditor got a call back:

```
summary(lm(unitAvail~race,data=housingData))
```

```
##
## Call:
## lm(formula = unitAvail ~ race, data = housingData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.8607  0.1393  0.1393  0.1843  0.1843
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.81574    0.01119  72.897  < 2e-16 ***
## racewhite    0.04498    0.01584   2.841  0.00455 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3677 on 2155 degrees of freedom
##   (5 observations deleted due to missingness)
## Multiple R-squared:  0.00373,    Adjusted R-squared:  0.003268
## F-statistic: 8.068 on 1 and 2155 DF,  p-value: 0.004546
```

```
summary(lm(unitInspec~race,data=housingData))
```

```
##
## Call:
## lm(formula = unitInspec ~ race, data = housingData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.5902 -0.5486  0.4098  0.4514  0.4514
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.54857    0.01505  36.440   <2e-16 ***
## racewhite    0.04163    0.02129   1.955   0.0507 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.495 on 2160 degrees of freedom
## Multiple R-squared:  0.001767,   Adjusted R-squared:  0.001305
## F-statistic: 3.823 on 1 and 2160 DF,  p-value: 0.05067
```

```
summary(lm(callBack~race,data=housingData))
```

```
##
## Call:
```

```
## lm(formula = callBack ~ race, data = housingData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.5106 -0.4181 -0.4181  0.4894  0.5819
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.41813    0.01511  27.672  < 2e-16 ***
## racewhite    0.09251    0.02137   4.329 1.57e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4968 on 2160 degrees of freedom
## Multiple R-squared:  0.008601,   Adjusted R-squared:  0.008142
## F-statistic: 18.74 on 1 and 2160 DF,  p-value: 1.567e-05
```

All three regressions show evidence of racial bias. For example, these regressions imply white auditors were 4.5% more likely to be told the unit was available, 4.1% more likely to inspect the unit, and 9.2% more likely to get a call back. Two of the three variables are statistically significant, meaning that it is not plausible that they are 0.

Fixed Effects

As discussed earlier, the matched nature of the study design means we don't have to control for Audit ID - an identifier for each audit. To demonstrate this, I've placed a large factor variable (aka a fixed effect) into the analysis. I have suppressed the output since there are so many results (over 600 coefficients!), but you can run the code below yourself.

```r
summary(lm(unitAvail~race+factor(auditID),data=housingData))
summary(lm(unitInspec~race+factor(auditID),data=housingData))
summary(lm(callBack~race+factor(auditID),data=housingData))
```

There are two observations to take away from this analysis. First, as expected, incorporating `auditID` did not affect the estimates of racial bias since each audit has one black and one white auditor. Put differently, no audit has a higher proportion of one race, and so race and this categorical variable are uncorrelated. Therefore, its omission in the previous section did not cause a bias. In typical observational data, this is not the case.

Second, including large factor variables in a regression is not big deal. Students at your level rarely control for enough factors. Regression can handle this many variables and far more. Later in the class I will show you a package that allows regressions to handle even more fixed effects that this.

Interaction Effects

To help understand what factors influence racial discrimination, we can include interaction terms in our regression. In this case, we will interact the race of the auditor with whether the auditor was a part of a couple. This will yield 4 coefficient estimates. Note, relative to the previous regressions, that the interpretation of these coefficients is changed when we include other independent variables.

1. A constant. As always, this represents our expectation when all independent variables are set to 0. In this case, it represents what we would expect to happen to a single black auditor.
2. The `race` coefficient. This represents how our expectation changes when we move from the default race (a black auditor) to a white auditor when the other values are set to their default value. In this case, this tells us how our expectation changes for *single* auditors.

3. The `auditorCouple` coefficient. This represents how our exepectation changes when we move from the default (a single auditor) to a couple when the other values are set to their default value. In this case, this tells us how our expectation changes for *black* auditors.
4. The `racewhite:auditorCouple` coefficient. This tells you how the effect of race changes when the auditor is in a couple. Equivalently, it tells us how the effect of being in a couple changes when the auditor is white. Both interpretations are valid and correct.

When interactions are present, the initial coefficients only apply to the default values of the other variables. We run the regressions below:

```r
summary(lm(unitAvail~race*auditorCouple,data=housingData))
```

```
##
## Call:
## lm(formula = unitAvail ~ race * auditorCouple, data = housingData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.8786  0.1418  0.1418  0.1746  0.2549
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)              0.74513    0.03232  23.058  < 2e-16 ***
## racewhite                0.13347    0.04561   2.926  0.00347 **
## auditorCouple            0.08033    0.03449   2.329  0.01995 *
## racewhite:auditorCouple -0.10069    0.04870  -2.068  0.03880 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3674 on 2153 degrees of freedom
##   (5 observations deleted due to missingness)
## Multiple R-squared:  0.006395,   Adjusted R-squared:  0.005011
## F-statistic: 4.619 on 3 and 2153 DF,  p-value: 0.003166
```

```r
summary(lm(unitInspec~race*auditorCouple,data=housingData))
```

```
##
## Call:
## lm(formula = unitInspec ~ race * auditorCouple, data = housingData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.5979 -0.5705  0.4021  0.4295  0.6109
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)              0.38914    0.04338   8.971  < 2e-16 ***
## racewhite                0.14529    0.06123   2.373   0.0177 *
## auditorCouple            0.18133    0.04629   3.917 9.25e-05 ***
## racewhite:auditorCouple -0.11784    0.06536  -1.803   0.0716 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4932 on 2158 degrees of freedom
## Multiple R-squared:  0.009676,   Adjusted R-squared:  0.0083
```

```
## F-statistic: 7.029 on 3 and 2158 DF,  p-value: 0.0001059
```

```r
summary(lm(callBack~race*auditorCouple,data=housingData))
```

```
##
## Call:
## lm(formula = callBack ~ race * auditorCouple, data = housingData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.5543 -0.4193 -0.4176  0.4954  0.5901
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)             0.409847   0.043703   9.378   <2e-16 ***
## racewhite               0.144479   0.061687   2.342   0.0193 *
## auditorCouple           0.009423   0.046641   0.202   0.8399
## racewhite:auditorCouple -0.059165   0.065851  -0.898   0.3690
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4969 on 2158 degrees of freedom
## Multiple R-squared:  0.009146,   Adjusted R-squared:  0.007768
## F-statistic: 6.639 on 3 and 2158 DF,  p-value: 0.0001839
```

In the first analysis, the `racewhite` coefficient tells us that a *single* white auditor was 13.3% more likely than a single black auditor to be told that the unit was available. The `auditorCouple` coefficient tells us that a black couple is 8% more likely to be told the unit was available. Finally the `racewhite:auditorCouple` tells us that, relative to a white couple, a black couple is 13.3% - 10% = 3.3% less likely to receive than a callback. Put differently, we learn that, according to this measure, single black auditors faced more discrimination than black auditors in a couple.

The findings are qualitatively similar for unit inspections. However, in the case of call backs, we can see the interaction term is no longer significiant, meaning that we don't know whether single black auditors faced more discrimination in this case.

Coefficient Interpretation

One might be curious about whether the effect of racial discrimination is moderated by the agent each auditor saw. That is, it is possible black auditors were assignment agents who were less likely to show apartments, or call their clients back.

One way to account for this is with an interaction between the effect of race, and whether the two auditors saw the same agent. However, one must be very careful about the interpretation of this regression. Suppose we found that indeed the agents that black auditors saw were worse than the ones white auditors saw. This would still qualify as racial discrimination, even if the race coefficient itself becomes insignificant. (Yinger 1986) clarifies:

> If ... agent assignment depends on the customer's minority status, then differences in teammates' treatment due to the assignment process constitute discrimination

When we include this interaction, the `race` coefficient *only* represents how discriminatory the process is when the auditors had different agents, rather that the racial discrimination of the entire process. The primary reason to run this regression is to help determine the mechanism, given that we established the overall effect in previous anlaysis.

We run the regressions below[3]:

```r
summary(lm(unitAvail~race*(sameAgent>0),data=housingData))
```

```
##
## Call:
## lm(formula = unitAvail ~ race * (sameAgent > 0), data = housingData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.8724  0.1276  0.1489  0.1835  0.1852
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  0.814815   0.016686  48.833   <2e-16 ***
## racewhite                    0.057613   0.023597   2.442   0.0147 *
## sameAgent > 0TRUE            0.001684   0.022499   0.075   0.9404
## racewhite:sameAgent > 0TRUE -0.023012   0.031837  -0.723   0.4699
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3678 on 2153 degrees of freedom
##   (5 observations deleted due to missingness)
## Multiple R-squared:  0.004147,   Adjusted R-squared:  0.00276
## F-statistic: 2.989 on 3 and 2153 DF,  p-value: 0.02996
```

```r
summary(lm(unitInspec~race*(sameAgent>0),data=housingData))
```

```
##
## Call:
## lm(formula = unitInspec ~ race * (sameAgent > 0), data = housingData)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.5976 -0.5524  0.4024  0.4476  0.4546
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                  0.552361   0.022437  24.618   <2e-16 ***
## racewhite                    0.028747   0.031731   0.906    0.365
## sameAgent > 0TRUE           -0.006907   0.030268  -0.228    0.820
## racewhite:sameAgent > 0TRUE  0.023441   0.042806   0.548    0.584
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4951 on 2158 degrees of freedom
## Multiple R-squared:  0.001929,   Adjusted R-squared:  0.0005415
## F-statistic:  1.39 on 3 and 2158 DF,  p-value: 0.2439
```

```r
summary(lm(callBack~race*(sameAgent>0),data=housingData))
```

```
##
## Call:
## lm(formula = callBack ~ race * (sameAgent > 0), data = housingData)
##
```

[3] I write `sameAgent>0` as some records have a value of 2 for this variable.

```
## Residuals:
##     Min      1Q  Median      3Q     Max
## -0.5303 -0.4209 -0.4148  0.5133  0.5852
##
## Coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 0.414784   0.022512  18.425   <2e-16 ***
## racewhite                   0.071869   0.031837   2.257   0.0241 *
## sameAgent > 0TRUE           0.006091   0.030369   0.201   0.8411
## racewhite:sameAgent > 0TRUE 0.037559   0.042949   0.875   0.3819
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.4968 on 2158 degrees of freedom
## Multiple R-squared:  0.009568,   Adjusted R-squared:  0.008191
## F-statistic: 6.949 on 3 and 2158 DF,  p-value: 0.0001186
```

Ultimately, we find that including this interaction did not qualitatively change our findings. This implies that the racial bias was within the treatment a particular agent gave auditors, rather than in the assignment of agents.

This concludes a brief dive into this dataset. I encourage you to explore this data, or the original data source, and test your own theories.

#References

Yinger, John. 1986. "Measuring Racial Discrimination with Fair Housing Audits: Caught in the Act." *The American Economic Review*, 881–93.