Getting Started

Load the usual packages (which should now include huxtable!).

```
library(tidyverse)
library(huxtable)
```

We will be using the gss dataset for this review. Load the `gssr` package, the gss_doc documentation, and the gss_all dataframe.

```
library(gssr)
```

```
## Package loaded. To attach the GSS data, type data(gss_all) at the console.
## For the codebook, type data(gss_doc). The gss_all and gss_doc objects will then be av
```

```
data(gss_doc)
data(gss_all)
```

Create a new dataframe called review. Filter the gss_all dataframe to keep only those observations from the 2010 waves and after. Select the variables we want.

```
review <- gss_all |>
  filter(year>=2010) |>
  select(year, intspace, consci, relig16, race, hispanic,
         sex, educ, age, id)
```

Clean Up

The big thing to do before starting analyses is to confirm that all missing values as NA. Run a summary of the review dataframe to make sure NAs have been captured.

```
summary(review)
```

```
##       year         intspace        consci         relig16           race
##  Min.   :2010   Min.   :1.00   Min.   :1.000   Min.   : 1.000   Min.   :1.000
##  1st Qu.:2012   1st Qu.:2.00   1st Qu.:1.000   1st Qu.: 1.000   1st Qu.:1.000
##  Median :2014   Median :2.00   Median :2.000   Median : 1.000   Median :1.000
##  Mean   :2014   Mean   :2.08   Mean   :1.643   Mean   : 2.008   Mean   :1.361
##  3rd Qu.:2016   3rd Qu.:3.00   3rd Qu.:2.000   3rd Qu.: 2.000   3rd Qu.:2.000
##  Max.   :2018   Max.   :3.00   Max.   :3.000   Max.   :13.000   Max.   :3.000
##                 NA's   :6287   NA's   :4188    NA's   :75
```

```
##     hispanic           sex             educ            age
##  Min.   : 1.000   Min.   :1.000   Min.   : 0.00   Min.   :18.00
##  1st Qu.: 1.000   1st Qu.:1.000   1st Qu.:12.00   1st Qu.:34.00
##  Median : 1.000   Median :2.000   Median :13.00   Median :48.00
##  Mean   : 1.692   Mean   :1.554   Mean   :13.64   Mean   :48.72
##  3rd Qu.: 1.000   3rd Qu.:2.000   3rd Qu.:16.00   3rd Qu.:62.00
##  Max.   :50.000   Max.   :2.000   Max.   :20.00   Max.   :89.00
##  NA's   :33                       NA's   :20      NA's   :34
##        id
##  Min.   :   1
##  1st Qu.: 589
##  Median :1178
##  Mean   :1201
##  3rd Qu.:1767
##  Max.   :2867
##
```

Recall that you can use the `gss_get_marginals()` function with `gss_doc` to see the labels for specific variables.

```
gss_get_marginals(varnames = c("intspace", "consci", "relig16", "race", "hispanic",
                               "sex", "educ", "age"), data = gss_doc) |>
  select(id, percent, n, value, label)
```

Let's combine values from the `race` and `hispanic` variables to make a new variable called `racehisp`. The easiest way to do this is to first make a binary variable distinguishing those who are not Hispanic from those who are.

```
review <- review |>
     mutate(anyhispanic = ifelse(hispanic==1, 0, 1))
```

Now we can combine values from this new `anyhispanic` variable and the race variable to create the racehisp categories:

```
review <- review |>
     mutate(racehisp = ifelse(anyhispanic==1, 4, race),
            racehisp = factor(racehisp,
                              labels = c("White", "Black", "Other", "Hispanic")))
```

Sometimes it's easier to create new variables instead of changing the values and labels of existing variables. Here we'll create new variables called `science` (taking the values of `consci`) and `space` (taking the values of `intspace`).

```
review <- review |>
     mutate(science = factor(consci,
                             levels = c(3, 2, 1),
                             labels = c("Hardly any", "Only some",
                                        "A great deal")),
            space = factor(intspace,
                           levels = c(3, 2, 1),
                           labels = c("Not interested",
                                      "Moderately interested",
                                      "Very interested")))
```

We can also collapse existing categories into bigger categories. We'll use the `relig16` variable as an example, creating a new variable called `religion` with broader categories.

```
table(review$relig16)
```

```
##
##    1    2    3    4    5    6    7    9   10   11   12   13
## 6102 3827  199 1007   64   51   60   74   55  244    9    4
```

Here we'll put all the respondents with values of 6-9 in the "Eastern" category, and those who are not Eastern, Protestant, Catholic, Jewish, or None in "Other":

```
review <- review |>
     mutate(religion = ifelse(relig16 == 1, "Protestant",
          ifelse(relig16 == 2, "Catholic",
          ifelse(relig16 == 3, "Jewish",
          ifelse(relig16 == 4, "None",
          ifelse(relig16 %in% 6:9, "Eastern", "Other"))))),
               religion = factor(religion,
                    levels = c("Protestant", "Catholic", "Jewish",
                               "Eastern", "Other", "None")))
```

Three Way Table

For each religious category, we want to know the proportion with each level of confidence in science who are in each category of interest in space. One way to do this is with `group_by()` and `summarize()`. For that approach, we would need binary variables for each of the `space` categories. This might seem tedious, but in the long run it is more efficient since it will allow you to manipulate the variables for other purposes later.

```
review <- review |>
     mutate(space_not_interested =
                  ifelse(space=="Not interested",1,0),
            space_moderately_interested =
                  ifelse(space=="Moderately interested",1,0),
            space_very_interested =
                  ifelse(space=="Very interested",1,0))
```

For each combination of `religion` and `science`, we can now summarize the means of each space binary variable (which represent the proportion of respondents in the related category of space interest):

```
space_summary <- review |>
     group_by(religion, science) |>
     summarize(not_interested =
                    round(mean(space_not_interested, na.rm=TRUE),3),
               moderately_interested =
                    round(mean(space_moderately_interested, na.rm=TRUE),3),
               very_interested =
                    round(mean(space_very_interested, na.rm=TRUE),3))
```

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

```
space_summary
```

```
## # A tibble: 28 x 5
## # Groups:   religion [7]
##    religion   science      not_interested moderately_interested very_interested
##    <fct>      <fct>                 <dbl>                 <dbl>           <dbl>
##  1 Protestant Hardly any            0.596                 0.288           0.116
##  2 Protestant Only some             0.354                 0.493           0.153
##  3 Protestant A great deal          0.207                 0.474           0.319
##  4 Protestant <NA>                  0.342                 0.459           0.2
##  5 Catholic   Hardly any            0.585                 0.264           0.151
##  6 Catholic   Only some             0.346                 0.47            0.184
##  7 Catholic   A great deal          0.22                  0.445           0.335
##  8 Catholic   <NA>                  0.313                 0.449           0.238
##  9 Jewish     Hardly any            0.5                   0.5             0
## 10 Jewish     Only some             0.161                 0.581           0.258
## # ... with 18 more rows
```

Those NAs for `science` and `religion` are annoying. One way to get rid of them is to filter them out. You can do that with an extra line in the chunk above. But we'll redo the whole chunk to compare them, though note it's not necessary to run this twice:

```
space_summary <- review |>
     filter(!is.na(science), !is.na(religion)) |>
     #Keep the observations that are not na for science or religion
     group_by(religion, science) |>
     summarise(not_interested = round(mean(space_not_interested,
                                           na.rm=TRUE),3),
               moderately_interested = round(mean(space_moderately_interested,
                                            na.rm=TRUE),3),
               very_interested = round(mean(space_very_interested,
                                            na.rm=TRUE),3))
```

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

```
space_summary
```

```
## # A tibble: 18 x 5
## # Groups:   religion [6]
##    religion   science      not_interested moderately_interested very_interested
##    <fct>      <fct>                 <dbl>                 <dbl>           <dbl>
##  1 Protestant Hardly any            0.596                 0.288           0.116
##  2 Protestant Only some             0.354                 0.493           0.153
##  3 Protestant A great deal          0.207                 0.474           0.319
##  4 Catholic   Hardly any            0.585                 0.264           0.151
##  5 Catholic   Only some             0.346                 0.47            0.184
##  6 Catholic   A great deal          0.22                  0.445           0.335
##  7 Jewish     Hardly any            0.5                   0.5             0
##  8 Jewish     Only some             0.161                 0.581           0.258
##  9 Jewish     A great deal          0.167                 0.633           0.2
## 10 Eastern    Hardly any            0.5                   0               0.5
## 11 Eastern    Only some             0.2                   0.4             0.4
## 12 Eastern    A great deal          0.2                   0.333           0.467
## 13 Other      Hardly any            0.4                   0.6             0
## 14 Other      Only some             0.472                 0.321           0.208
## 15 Other      A great deal          0.184                 0.469           0.347
## 16 None       Hardly any            0.455                 0.242           0.303
## 17 None       Only some             0.352                 0.496           0.152
## 18 None       A great deal          0.23                  0.378           0.393
```

You can clean up the column names of this table and pander it before you knit. Note that you can also add a table caption in the pander function.

Dealing With NAs In Other Functions

For mean and standard deviation, remove NAs by adding `na.rm = TRUE`:

```
mean(review$age)
```

```
## [1] NA
```

```
mean(review$age, na.rm = TRUE)
```

```
## [1] 48.72003
```

```
sd(review$educ)
```

```
## [1] NA
```

```
sd(review$educ, na.rm = TRUE)
```

```
## [1] 3.05107
```

For correlation, restrict the estimation to cases with values for both variables by adding `use = "complete"`:

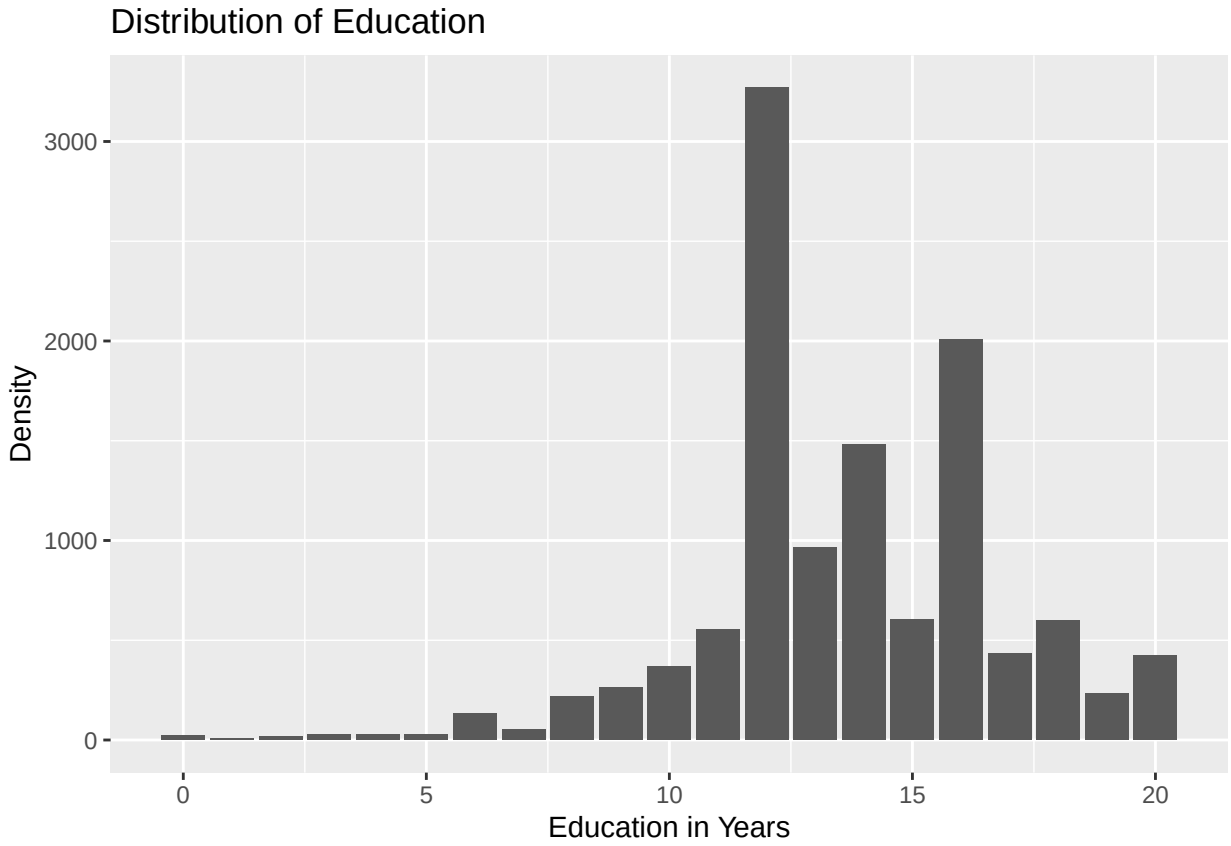
```
cor(review$age, review$educ, use = "complete")
```

```
## [1] -0.0319707
```

For ggplot, R knows to only use complete cases but will warn you that it is doing so. To drop the warning, add `warning = FALSE` to the start of the code chunk:

```
plot <- ggplot(review, aes(x = educ))
plot + geom_bar() +
  labs(x = "Education in Years",
       y = "Density",
       title = "Distribution of Education",
       saubtitle = "General Social Survey, 2010-2018")
```

```
## Don't know how to automatically pick scale for object of type haven_labelled. Default
```



Remember to change the axis labels and add a title to the figure above!

Basic linear models also know to drop NAs. The notes section of the summary informs you how many cases have been deleted from the estimates (in the example below, 4210 observations are deleted due to missingness).

This is new: notice how we are redefining the science factor variable to have a numeric scale in the chunk below. Each of the three factor levels will be assigned a number from 1-3. Since we asserted that the order of levels is "Hardly any" / "Only some" / "A great deal", now higher scores tell us that respondents have more confidence in scientific institutions. (This is a neat trick, but in general be careful with this approach. It only works if you can assume that the distance between each level is even.)

```
model <- lm(as.numeric(science) ~ religion * educ, data = review)
summary(model)
```

```
##
## Call:
## lm(formula = as.numeric(science) ~ religion * educ, data = review)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
```

```
## -1.7640 -0.4016 -0.2361  0.5875  1.1920
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)              1.722383   0.047082  36.583  < 2e-16 ***
## religionCatholic         0.236068   0.068917   3.425 0.000617 ***
## religionJewish           0.242668   0.336750   0.721 0.471166
## religionEastern          0.512880   0.258559   1.984 0.047336 *
## religionOther            0.202906   0.197753   1.026 0.304898
## religionNone            -0.076324   0.117113  -0.652 0.514607
## educ                     0.042810   0.003366  12.720  < 2e-16 ***
## religionCatholic:educ   -0.010376   0.004931  -2.104 0.035406 *
## religionJewish:educ     -0.005113   0.020718  -0.247 0.805068
## religionEastern:educ    -0.022944   0.017004  -1.349 0.177282
## religionOther:educ      -0.006174   0.014288  -0.432 0.665674
## religionNone:educ        0.013085   0.008352   1.567 0.117259
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5901 on 7510 degrees of freedom
##   (4249 observations deleted due to missingness)
## Multiple R-squared:  0.04837,    Adjusted R-squared:  0.04698
## F-statistic:  34.7 on 11 and 7510 DF,  p-value: < 2.2e-16
```

Use huxreg with this model for your final knitted version:

By default, the `fitted.values()` function will not work if there are NAs in your model. If you want to save predicted values from a model with missing values, add `na.action = na.exclude` to your `lm()` code. Now when you run the `fitted.values` function any observations not included in your model will have NA as their predicted value.

```
model <- lm(as.numeric(science) ~ educ,
            data = review,
            na.action=na.exclude) # Add to predict NA if observation has NAs

review$predicted_science <- fitted(model)

summary(review$predicted_science)
```

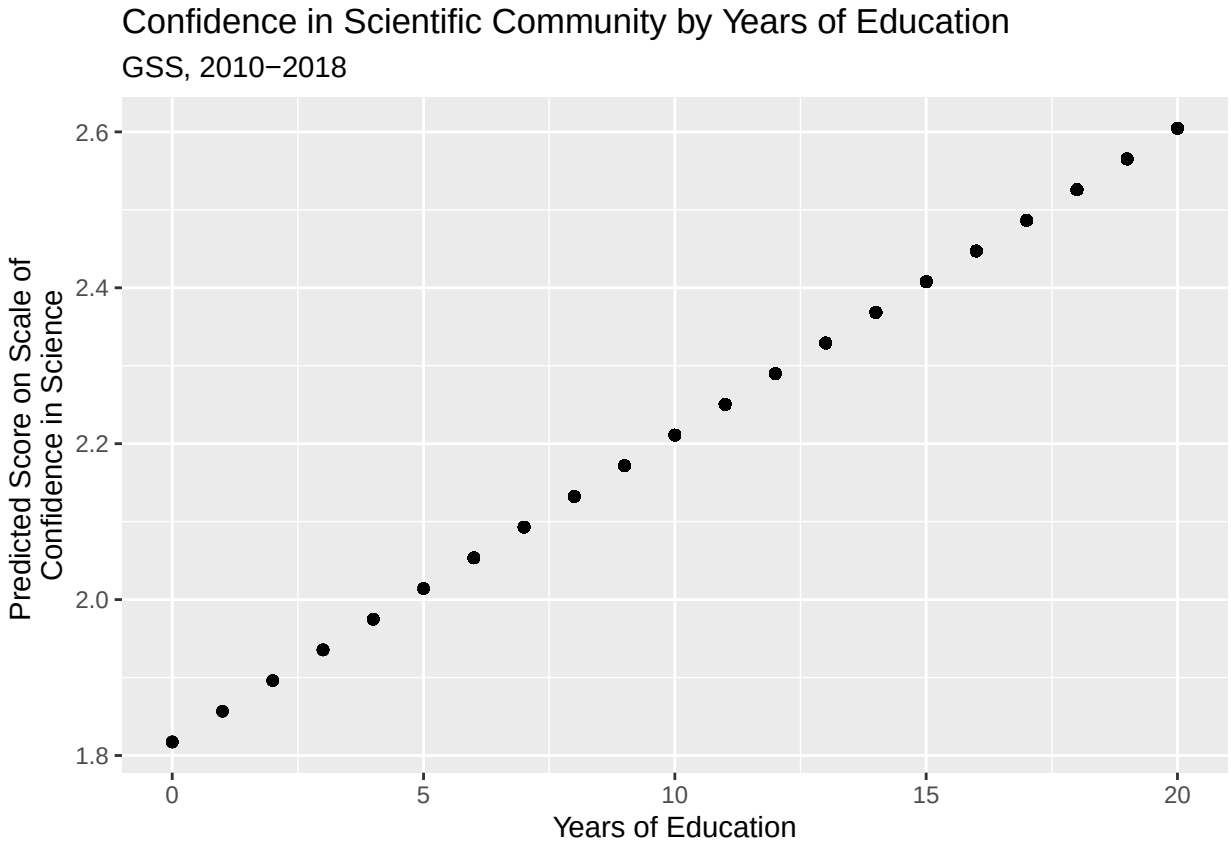
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##   1.817   2.290   2.368   2.357   2.447   2.605    4199
```

More Thoughts On Plotting

Always remember to label your axes and plots!

```
plot <- ggplot(review, aes(x = educ, y = predicted_science))
plot + geom_point() +
     labs(x = "Years of Education",
          y = "Predicted Score on Scale of \nConfidence in Science",
          title = "Confidence in Scientific Community by Years of Education",
          subtitle = "GSS, 2010-2018")
```

```
## Don't know how to automatically pick scale for object of type haven_labelled. Default
```



Using Markdown For Reports

Hiding Code and Inline Code

Let's start with a case where your output is a single number, like a mean. Imagine you are working on the descriptives part of your project and want to include the mean of age. The place to start is with a regular code chunk with the `mean()` function:

```
mean(review$age, na.rm=TRUE)
```

```
## [1] 48.72003
```

But say you want R to run a code chunk and have only the output - not the code! - show up in your file. Simply add `echo = FALSE` to the first fence:

```
## [1] 48.72003
```

If you want to integrate a single number into your document, you can use inline code. Without opening a full code chunk, just use one backtick to open and close your fence. Then write a sentence as you normally would, and let R Markdown replace your code with the output:

The mean of age is 48.72.

Other Options For Hiding Code

If you want to run the code chunk so you can see the output in your notebook but with neither the code nor the output showing up in your knitted file, use `include = FALSE`.

```
## [1] 48.72003
```

I would probably recommend starting with `include = FALSE` for your final project, so you can see all your output but then selectively choose what to include and what not to include in your knitted report.

If for some reason you want to show the code but not the output, use `eval = FALSE`.

```
mean(review$age, na.rm=TRUE)
```

R Markdown Tips

Some other things to know about writing in R Markdown...

Use hashtags for headings. One hashtag is for a big heading; additional hashtags shrink the size. For example:

Biggest Heading

Big Heading

Small Heading

Smallest Heading

If you want to italicize text, *wrap it within single asterisks*. If you want to bold text, **wrap it within double asterisks**. And if you want to italicize *and* bold text, ***wrap it within triple asterisks***.

It can sometimes be helpful to highlight original variable names or unusual terms within tickmarks. But note this is similar to the inline code we saw earlier. As long as the word or phrase does not start with a single r, R will not try to run it as code. See the preview file for the difference in what these tickmarks represent:

The mean of `age` is 48.72.

To create an ordered list, leave an empty line and then:

- Start
- Each
- Item
- With
- A
- Dash

To create a numbered list, leave an empty line and then:

1. Start
2. Each
3. Item
4. With
5. A
6. Number and a period

To add a horizontal line rule, include at least three dashes on a single line:

And to add a page break:

This should be the start of a new page!

It's Also The Start Of A New Section

Formatting Summary Tables

We have seen `huxtable()` and `huxreg()` a lot. They are great. Use them.

One additional way to use `huxtable()` is to combine it with `group_by()` and `summarize()` to make a nice summary table. Let's start with the code for getting means and standard deviations of the `age` and `educ` variables for each `religion` group:

If we huxtable this table, we'll have the religion categories in the rows and the means and standard deviations in the columns:

Note that `huxtable()` also works well with `t.test()` after asserting that the results should be in tidy format...

...and `prop.test()`...

...and `chisq.test()`...

...and `fisher.test()`...

```
## Warning in chisq.test(educ_11_years_only$religion, educ_11_years_only$space):
## Chi-squared approximation may be incorrect
```

```
##                              educ_11_years_only$space
## educ_11_years_only$religion Not interested Moderately interested
##                   Protestant     45.9183673            54.5918367
##                   Catholic       30.4897959            36.2489796
##                   Jewish          0.3673469             0.4367347
##                   Eastern         0.3673469             0.4367347
##                   Other           3.3061224             3.9306122
##                   None            9.5510204            11.3551020
##                              educ_11_years_only$space
## educ_11_years_only$religion Very interested
##                   Protestant      24.4897959
##                   Catholic        16.2612245
##                   Jewish           0.1959184
##                   Eastern          0.1959184
##                   Other            1.7632653
##                   None             5.0938776
```

id	percent	n	value	label
AGE				
SEX	44.1	28614	1	MALE
SEX	55.9	36200	2	FEMALE
SEX	100	64814		Total
RACE	80.3	52033	1	WHITE
RACE	14.2	9187	2	BLACK
RACE	5.5	3594	3	OTHER
RACE	100	64814		Total
HISPANIC	88.4	23555	1	NOT HISPANIC
HISPANIC	7.1	1885	2	MEXICAN, MEXICAN AMERICAN, CHICANO/A
HISPANIC	1.4	384	3	PUERTO RICAN
HISPANIC	0.5	130	4	CUBAN
HISPANIC	0.4	98	5	SALVADORIAN
HISPANIC	0.2	66	6	GUATEMALAN
HISPANIC	0.1	15	7	PANAMANIAN
HISPANIC	0.1	19	8	NICARAGUAN
HISPANIC	0	4	9	COSTA RICAN
HISPANIC	0.1	27	10	CENTRAL AMERICAN
HISPANIC	0.2	41	11	HONDURAN
HISPANIC	0.3	73	15	DOMINICAN
HISPANIC	0	1	16	WEST INDIAN
HISPANIC	0.1	27	20	PERUVIAN
HISPANIC	0.1	38	21	EQUADORIAN
HISPANIC	0.2	41	22	COLUMBIAN
HISPANIC	0.1	14	23	VENEZUELAN
HISPANIC	0	12	24	Argentinian
HISPANIC	0	4	25	Chilean
HISPANIC	0.5	136	30	SPANISH
HISPANIC	0	2	31	BASQUE
HISPANIC	0	7	35	FILIPINO/A

ligion	Confidence in Science	Space Interest = None	Space Interest = Moderate	Space Interest = Ve
otestant	Hardly any	0.596	0.288	0.116
otestant	Only some	0.354	0.493	0.153
otestant	A great deal	0.207	0.474	0.319
tholic	Hardly any	0.585	0.264	0.151
tholic	Only some	0.346	0.47	0.184
tholic	A great deal	0.22	0.445	0.335
vish	Hardly any	0.5	0.5	0
vish	Only some	0.161	0.581	0.258
vish	A great deal	0.167	0.633	0.2
stern	Hardly any	0.5	0	0.5
stern	Only some	0.2	0.4	0.4
stern	A great deal	0.2	0.333	0.467
ner	Hardly any	0.4	0.6	0
ner	Only some	0.472	0.321	0.208
ner	A great deal	0.184	0.469	0.347
ne	Hardly any	0.455	0.242	0.303
ne	Only some	0.352	0.496	0.152
ne	A great deal	0.23	0.378	0.393

Table 1: What is the title?

	(1)
(Intercept)	1.722 ***
	(0.047)
religionCatholic	0.236 ***
	(0.069)
religionJewish	0.243
	(0.337)
religionEastern	0.513 *
	(0.259)
religionOther	0.203
	(0.198)
religionNone	-0.076
	(0.117)
educ	0.043 ***
	(0.003)
religionCatholic:educ	-0.010 *
	(0.005)
religionJewish:educ	-0.005
	(0.021)
religionEastern:educ	-0.023
	(0.017)
religionOther:educ	-0.006
	(0.014)
religionNone:educ	0.013
	(0.008)
N. obs.	7522

*** p < 0.001; ** p < 0.01; * p < 0.05.

Table 2: Summary Table: Age and Education by Religion

Religion	**Age Mean**	**Age SD**	**Education Mean**	**Education SD**
Protestant	51	17.9	13.7	2.81
Catholic	47.9	17.1	13.5	3.35
Jewish	56.2	18	16	2.67
Eastern	41.6	16.4	15.2	3.38
Other	38.4	15.4	13.4	2.68
None	41.6	16	13.6	3.07

Table 3: T Test: Difference in Mean Age between Jewish and Eastern Respondents

estimate	estimate1	estimate2	statistic	p.value	parameter	conf.low	conf.high	alternative
14.7	56.2	41.6	8.33	1.5e-15	380	11.2	18.1	two.sided

Table 4: Proportion Test: Protestant vs No Religion and Very Interested in Space

estimate1	estimate2	statistic	p.value	parameter	conf.low	conf.high	alternative
0.791	0.714	14	0.000186	1	0.0333	0.122	two.sided

Table 5: Chi-square Test: Sex and Confidence in Science

statistic	p.value	parameter
60.4	7.81e-14	2

Table 6: Fisher Test: Religion and Interest in Space

p.value	alternative
0.0365	two.sided