

## 432 Class 03

<https://thomaseLove.github.io/432-2024/>

2024-01-23

# Today's Agenda

## Incorporating Survey Weights ...

- 1 In estimating means and confidence intervals
- 2 In building linear regression models
- 3 Into a more detailed t-test approach using NHANES

Primary Source:

<https://bookdown.org/rwnahhas/RMPH/survey-design.html>

# Today's R Setup

```
knitr::opts_chunk$set(comment = NA)

library(broom)
library(janitor)
library(gtsummary)
library(gt)
library(mosaic)

library(nhanesA) # data source
library(survey) # survey-specific tools

library(tidyverse)

theme_set(theme_bw())
```

# Section 1

## Incorporating survey weights (an introduction)

# What are survey weights?

In many surveys, each sampled subject is assigned a weight that is equivalent to the reciprocal of his/her probability of selection into the sample.

$$\text{Sample Subject's Weight} = \frac{1}{\text{Prob}(\textit{selection})}$$

but more sophisticated sampling designs require more complex weighting schemes. Usually these are published as part of the survey data.

I'll demonstrate part of the survey package today.

# An NHANES Example

Let's use the NHANES 2013-14 data and pull in both the demographics (DEMO\_H) and total cholesterol (TCHOL\_H) databases.

```
demo_raw <- nhanes('DEMO_H', translated = FALSE)
tchol_raw <- nhanes('TCHOL_H', translated = FALSE)
```

Detailed descriptions available at

- [https://wwwn.cdc.gov/Nchs/Nhanes/2013-2014/DEMO\\_H.htm](https://wwwn.cdc.gov/Nchs/Nhanes/2013-2014/DEMO_H.htm)
- [https://wwwn.cdc.gov/Nchs/Nhanes/2013-2014/TCHOL\\_H.htm](https://wwwn.cdc.gov/Nchs/Nhanes/2013-2014/TCHOL_H.htm)

# Weighting in NHANES

Weights for each sampled person in NHANES account for the complex survey design. The weight describes the number of people in the population represented by the sampled person, and is created in three steps:

- 1 the base weight is computed, which accounts for the unequal probabilities of selection given that some demographic groups were over-sampled;
- 2 adjustments are made for non-response; and
- 3 post-stratification adjustments are made to match estimates of the U.S. civilian non-institutionalized population available from the Census Bureau.

Source: <https://wwwn.cdc.gov/nchs/nhanes/tutorials/Module3.aspx>

# Weights in our NHANES data

The DEMO file contains two kinds of sampling weights:

- the interview weight (WTINT2yr), and
- the MEC exam weight (WTMEC2yr)

NHANES also provides several weights for subsamples. In NHANES, we identify the variable of interest that was collected on the smallest number of respondents. The sample weight that applies to that variable is the appropriate one to use. In our first case, we will study total cholesterol and use the weights from the MEC exam.



# What Variables Do We Need?

- SEQN = subject identifying code
- RIAGENDR = sex (1 = M, 2 = F)
- RIDAGEYR = age (in years at screening, topcode at 80)
- DMQMILIZ = served active duty in US Armed Forces (yes/no)
- RIDSTATR = 2 if subject took both interview and MEC exam
- WTMEC2YR - Full sample 2 year MEC exam weight
- LBXTC = Total Cholesterol (mg/dl) - this is our outcome

The first 5 are in DEMO\_H, and the first and last are in TCHOL\_H.

## Merge the DEMO and TCHOL files

```
dim(demo_raw)
```

```
[1] 10175    47
```

```
dim(tchol_raw)
```

```
[1] 8291     3
```

```
joined_df <- inner_join(demo_raw, tchol_raw, by = c("SEQN"))
```

```
dim(joined_df)
```

```
[1] 8291    49
```

## Create a small analytic tibble

```
nh1314 <- joined_df |> # has n = 8291
  tibble() |>
  filter(complete.cases(LBXTC)) |> # now n = 7624
  filter(RIDSTATR == 2) |> # still 7624
  filter(RIDAGEYR > 19 & RIDAGEYR < 40) |> # now n = 1802
  filter(DMQMILIZ < 3) |> # drop 7 = refused, n = 1801
  mutate(FEMALE = RIAGENDR - 1,
         AGE = RIDAGEYR,
         US_MIL = ifelse(DMQMILIZ == 1, 1, 0),
         WT_EX = WTMEC2YR,
         TOTCHOL = LBXTC) |>
  select(SEQN, FEMALE, AGE, TOTCHOL, US_MIL, WT_EX)
```

## nh1314 analytic sample

```
nh1314 |> select(AGE, TOTCHOL, WT_EX) |> summary()
```

AGE		TOTCHOL		WT_EX	
Min.	:20.00	Min.	: 69	Min.	: 8430
1st Qu.:	24.00	1st Qu.:	156	1st Qu.:	24694
Median	:30.00	Median	:178	Median	: 34642
Mean	:29.47	Mean	:181	Mean	: 44529
3rd Qu.:	34.00	3rd Qu.:	203	3rd Qu.:	59561
Max.	:39.00	Max.	:417	Max.	:125680

```
nh1314 |> tabyl(FEMALE, US_MIL) |>  
  adorn_totals(where = c("row", "col")) |> adorn_title()
```

		US_MIL		
FEMALE	0	1	Total	
0	829	45	874	
1	921	6	927	
Total	1750	51	1801	

## Formatting df\_stats with gt()

```
df_stats(~ AGE + TOTCHOL, data = nh1314) |>
  mutate(across(mean:sd, ~ round_half_up(.x, 2))) |>
  gt() |> tab_options(table.font.size = 20) |>
  tab_header(title = "Approach A",
             subtitle = "Data from nh1314 sample, unadjusted")
```

### Approach A

Data from nh1314 sample, unadjusted

response	min	Q1	median	Q3	max	mean	sd	n	m
AGE	20	24	30	34	39	29.47	5.80	1801	
TOTCHOL	69	156	178	203	417	181.01	37.41	1801	

## Formatting df\_stats with gt()

```
df_stats(~ AGE + TOTCHOL, data = nh1314) |>
  gt() |> fmt_number(columns = mean:sd, decimals = 2) |>
  tab_options(table.font.size = 20) |>
  tab_header(title = "Approach B",
             subtitle = "Data from nh1314 sample, unadjusted")
```

Approach B  
Data from nh1314 sample, unadjusted

response	min	Q1	median	Q3	max	mean	sd	n	m
AGE	20	24	30	34	39	29.47	5.80	1801	
TOTCHOL	69	156	178	203	417	181.01	37.41	1801	

## Our nh1314 analytic sample: Weights

Each weight represents the number of people exemplified by that subject.

```
favstats(~ WT_EX, data = nh1314) |>  
  rename(na = missing) |> gt() |>  
  tab_options(table.font.size = 20)
```

min	Q1	median	Q3	max	mean	
8430.461	24694.05	34642.05	59560.74	125680.3	44528.66	26027

## Using gtsummary() to describe nh1314 (unweighted)

```
table1 <- nh1314 |>  
  tbl_summary(include = -SEQN)
```

table1

Characteristic	N = 1,801
FEMALE	927 (51%)
AGE	30.0 (24.0, 34.0)
TOTCHOL	178 (156, 203)
US_MIL	51 (2.8%)
WT_EX	34,642 (24,694, 59,561)

See <https://www.danielsjoberg.com/gtsummary/> for more options.



## Create nh\_design survey design

```
nh_design <-  
  svydesign(  
    id = ~ SEQN,  
    weights = ~ WT_EX,  
    data = nh1314)  
  
nh_design <- update( nh_design, one = 1)  
  
## this one = 1 business will help us count  
  
nh_design
```

Independent Sampling design (with replacement)  
`update(nh_design, one = 1)`

# Unweighted Counts

## Overall

```
sum(weights(nh_design, "sampling") != 0)
```

```
[1] 1801
```

## By Groups

```
svyby( ~ one, ~ FEMALE, nh_design, unwtd.count)
```

	FEMALE	counts	se
0	0	874	0
1	1	927	0

```
svyby( ~ one, ~ FEMALE + US_MIL, nh_design, unwtd.count)
```

	FEMALE	US_MIL	counts	se
0.0	0	0	829	0
1.0	1	0	921	0

# Weighted Counts

```
svytotal( ~ one, nh_design )
```

	total	SE
one	80196108	1104558

## By Groups

```
svyby( ~ one, ~ FEMALE, nh_design, svytotal)
```

	FEMALE	one	se
0	0	39694756	1255122
1	1	40501352	1196260

```
svyby( ~ one, ~ FEMALE * US_MIL, nh_design, svytotal)
```

	FEMALE	US_MIL	one	se
0.0	0	0	37185326.4	1225990.7
1.0	1	0	40151728.1	1192408.4

## Use survey design for weighted means

What is the mean of total cholesterol, overall and in groups?

```
svymean( ~ TOTCHOL, nh_design, na.rm = TRUE)
```

	mean	SE
TOTCHOL	181.25	1.0172

```
svyby(~ TOTCHOL, ~ FEMALE, nh_design, svymean, na.rm = TRUE)
```

	FEMALE	TOTCHOL	se
0	0	182.6313	1.515072
1	1	179.8881	1.359801

```
svyby(~ TOTCHOL, ~ FEMALE + US_MIL, nh_design, svymean, na.rm
```

	FEMALE	US_MIL	TOTCHOL	se
0.0	0	0	182.3569	1.575994
1.0	1	0	180.0248	1.368408

# Unweighted Summaries of TOTCHOL

```
favstats(~ TOTCHOL, data = nh1314) |>  
  mutate(se = sd / sqrt(n)) |>  
  gt() |> fmt_number(columns = c(mean, sd, se), decimals = 3)  
  tab_options(table.font.size = 20)
```

min	Q1	median	Q3	max	mean	sd	n	missing
69	156	178	203	417	181.012	37.408	1801	0

```
nh1314 |> group_by(FEMALE, US_MIL) |>  
  summarise(n = n(), mean = mean(TOTCHOL), se = sd(TOTCHOL)/sqrt(n))
```

```
# A tibble: 4 x 5  
# Groups:   FEMALE [2]  
  FEMALE US_MIL      n mean    se  
  <dbl> <dbl> <int> <dbl> <dbl>  
1      0      0   829  182.  1.33
```

# Survey-Weighted Measures of uncertainty

Mean of total cholesterol within groups with 90% CI?

```
grouped_result <- svyby(~ TOTCHOL, ~ FEMALE + US_MIL,  
                        nh_design, svymean, na.rm = TRUE)  
coef(grouped_result)
```

	0.0	1.0	0.1	1.1
	182.3569	180.0248	186.6966	164.1984

```
confint(grouped_result, level = 0.90)
```

	5 %	95 %
0.0	179.7646	184.9492
1.0	177.7739	182.2756
0.1	177.8887	195.5045
1.1	153.4489	174.9478

- Get standard errors with `se(grouped_result)`, too.

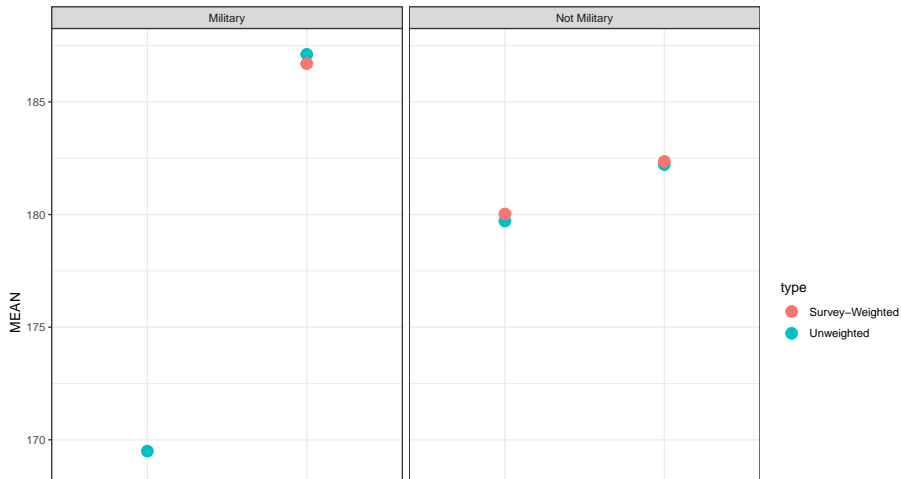
## Store estimated means in res

```
res <- tibble(  
  type = rep(c("Unweighted", "Survey-Weighted"), 4),  
  female = c(rep("Female", 4), rep("Male", 4)),  
  us_mil = rep(c("Military", "Military", "Not Military", "Not  
  MEAN = c(169.5, 164.1984, 179.71, 180.0248, 187.11, 186.6966  
  
res |> gt()
```

type	female	us_mil	MEAN
Unweighted	Female	Military	169.5000
Survey-Weighted	Female	Military	164.1984
Unweighted	Female	Not Military	179.7100
Survey-Weighted	Female	Not Military	180.0248
Unweighted	Male	Military	187.1100
Survey-Weighted	Male	Military	186.6966
Unweighted	Male	Not Military	182.2200
Survey-Weighted	Male	Not Military	182.3560

# Estimated Means, plotted

```
ggplot(res, aes(x = female, y = MEAN, col = type)) +  
  geom_point(size = 4) +  
  facet_wrap(~ us_mil)
```





## Section 2

### Building Models and Survey Weights

## Modeling TOTCHOL in nh1314

First, we'll ignore weighting, and fit a model with main effects of all three predictors (mod1), then a model (mod2) which incorporates an interaction of FEMALE and US\_MIL.

```
mod1 <- lm(TOTCHOL ~ AGE + FEMALE + US_MIL, data = nh1314)

mod2 <- lm(TOTCHOL ~ AGE + FEMALE * US_MIL, data = nh1314)
```

The interaction term means that the effect of FEMALE on TOTCHOL depends on the US\_MIL status.

## mod1, unweighted

```
tidy(mod1, conf.int = TRUE, conf.level = 0.90) |>  
  select(-statistic) |> gt() |> tab_options(table.font.size =
```

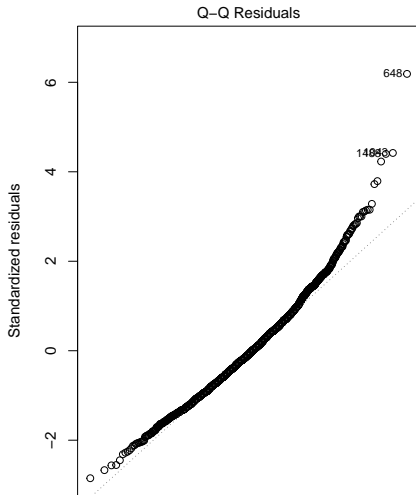
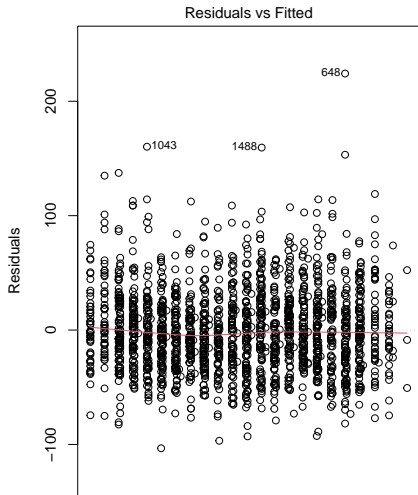
term	estimate	std.error	p.value	conf.low	conf.high
(Intercept)	136.345657	4.4915861	9.534649e-164	128.953845	143.737469
AGE	1.571367	0.1474222	9.149426e-26	1.328754	1.813979
FEMALE	-3.312433	1.7274350	5.532719e-02	-6.155276	-0.469590
US_MIL	2.003854	5.2026231	7.001628e-01	-6.558113	10.565821

```
glance(mod1) |> select(r2 = r.squared, adjr2 = adj.r.squared,  
  sigma, nobs, df) |> gt() |> tab_options(table.font.size =
```

r2	adjr2	AIC	BIC	sigma	nobs	df
0.06097646	0.0594088	18052.71	18080.19	36.27952	1801	3

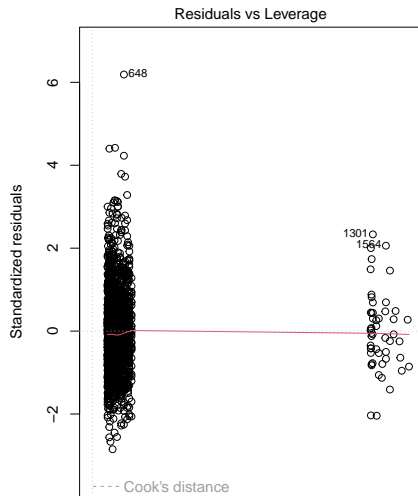
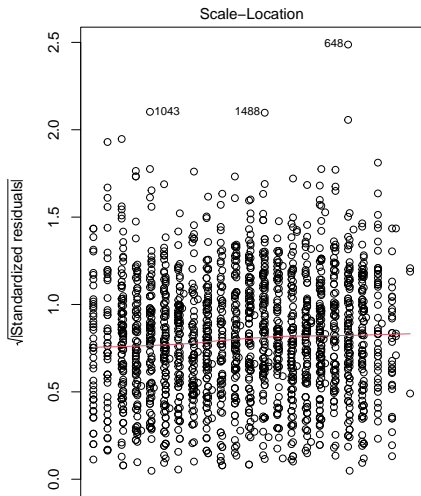
## mod1 Residuals (plots 1, 2)

```
par(mfrow = c(1,2)); plot(mod1, which = c(1,2))
```



## mod1 Residuals (plots 3, 5)

```
par(mfrow = c(1,2)); plot(mod1, which = c(3,5))
```



## mod2, unweighted

```
tidy(mod2, conf.int = TRUE, conf.level = 0.90) |>  
  select(-statistic) |> gt() |> tab_options(table.font.size = 12)
```

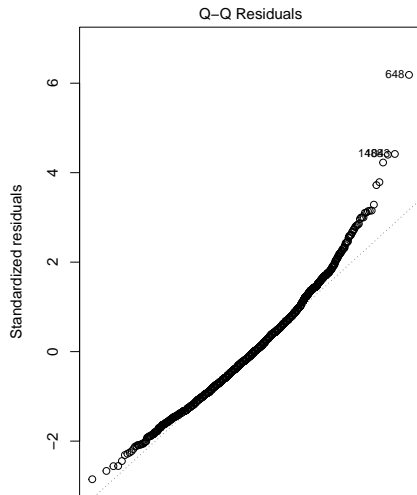
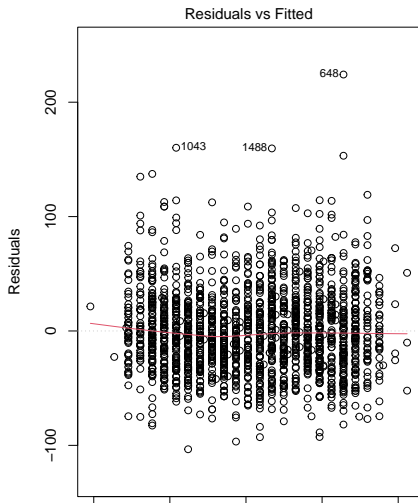
term	estimate	std.error	p.value	conf.lo
(Intercept)	136.299221	4.4922913	1.340759e-163	128.90624
AGE	1.570077	0.1474422	1.015235e-25	1.32743
FEMALE	-3.151959	1.7380814	6.992615e-02	-6.01232
US_MIL	3.639800	5.5547809	5.123873e-01	-5.50171
FEMALE:US_MIL	-13.342653	15.8650968	4.004561e-01	-39.45188

```
glance(mod2) |>  
  select(r2 = r.squared, adjr2 = adj.r.squared, AIC, BIC, sigma,  
         nobs, df) |> gt() |> tab_options(table.font.size = 20)
```

r2	adjr2	AIC	BIC	sigma	nobs	df
0.06124611	0.05025557	18054.1	18086.07	26.28248	1801	4

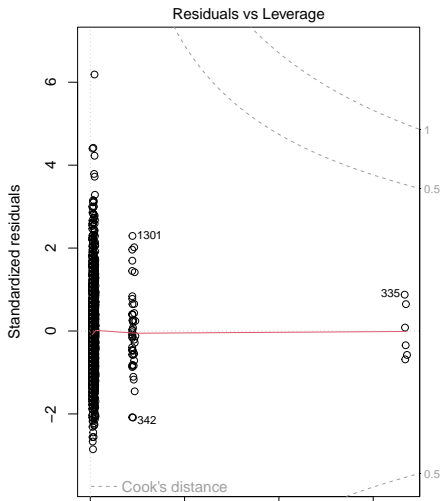
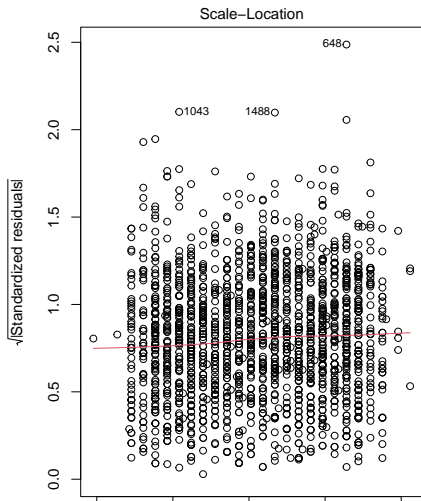
## mod2 Residuals (plots 1, 2)

```
par(mfrow = c(1,2)); plot(mod2, which = c(1,2))
```



## mod2 Residuals (plots 3, 5)

```
par(mfrow = c(1,2)); plot(mod2, which = c(3,5))
```





## Survey-weighted models via svyglm

Again, we'll run two models, first without and second with an interaction term between FEMALE and US\_MIL.

```
glm1_results <- svyglm(TOTCHOL ~ AGE + FEMALE + US_MIL,  
  nh_design, family = gaussian())
```

```
glm2_results <- svyglm(TOTCHOL ~ AGE + FEMALE * US_MIL,  
  nh_design, family = gaussian())
```

Gaussian family used to generate linear regressions here.

# Weighted Model 1

```
tidy(glm1_results, conf.int = TRUE, conf.level = 0.90) |>  
  select(-statistic) |> gt() |> tab_options(table.font.size =
```

term	estimate	std.error	p.value	conf.low	conf.high
(Intercept)	137.1292664	5.0039123	1.906826e-138	128.894318	145.364215
AGE	1.5646634	0.1696597	7.889576e-20	1.285454	1.843872
FEMALE	-3.2123089	2.0091506	1.100321e-01	-6.518772	0.094154
US_MIL	0.5935502	5.0392343	9.062506e-01	-7.699528	8.886631

```
glance(glm1_results) |> select(nobs, AIC, BIC, everything()) |>  
  gt() |> tab_options(table.font.size = 20)
```

nobs	AIC	BIC	null.deviance	df.null	deviance	df.residual
1801	21.6033	2344965	2498023	1800	2344935	1797

## Weighted Model 2

```
tidy(glm2_results, conf.int = TRUE, conf.level = 0.90) |>  
  select(-statistic) |> gt() |> tab_options(table.font.size =
```

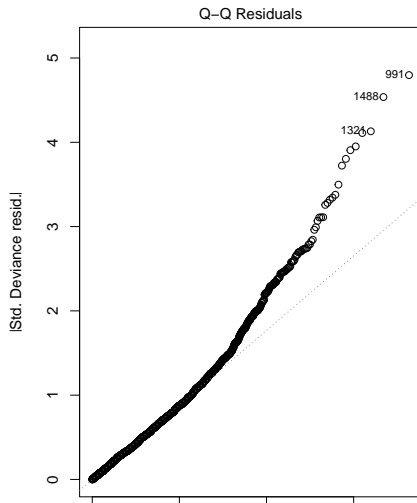
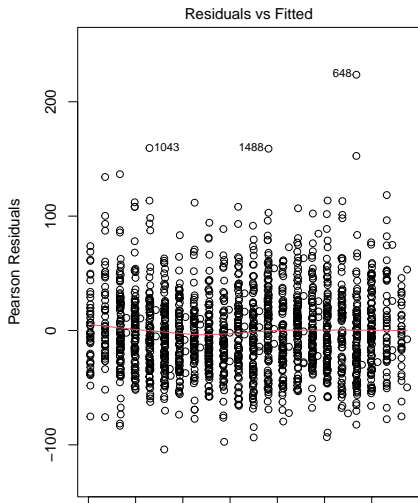
term	estimate	std.error	p.value	conf.low
(Intercept)	136.863878	5.0060799	6.872607e-138	128.625359
AGE	1.567633	0.1695865	6.517529e-20	1.288544
FEMALE	-2.868135	2.0285450	1.575681e-01	-6.206517
US_MIL	3.426681	5.4709976	5.311744e-01	-5.576953
FEMALE:US_MIL	-22.065349	8.5522325	9.956850e-03	-36.139779

```
glance(glm2_results) |> select(nobs, AIC, BIC, everything())  
  gt() |> tab_options(table.font.size = 20)
```

nobs	AIC	BIC	null.deviance	df.null	deviance	df.residual
1801	22.19935	2341671	2498023	1800	2341633	1796

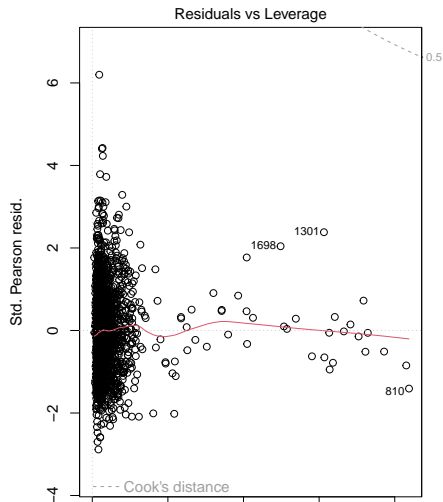
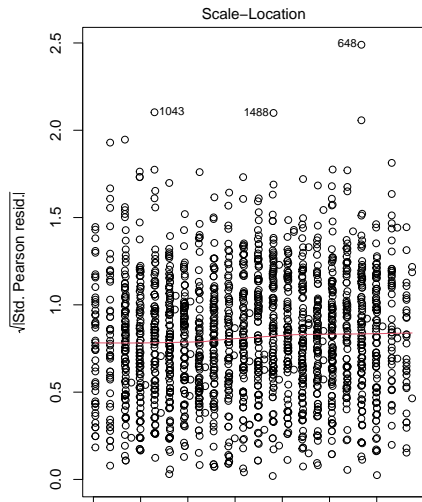
# Residuals for Model glm1\_results

```
par(mfrow = c(1,2)); plot(glm1_results, which = c(1,2))
```

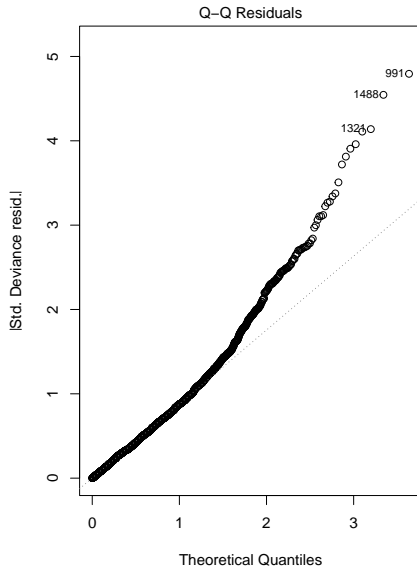
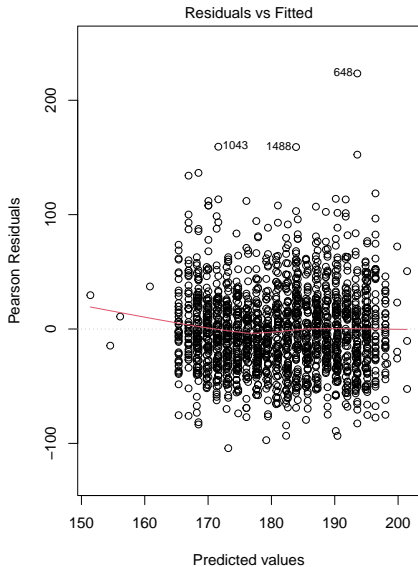


# Residuals for Model glm1\_results

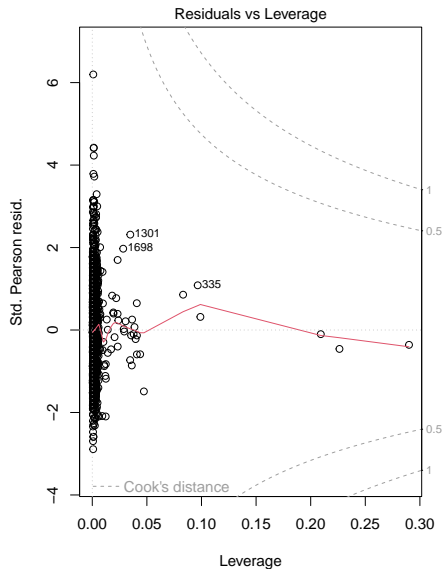
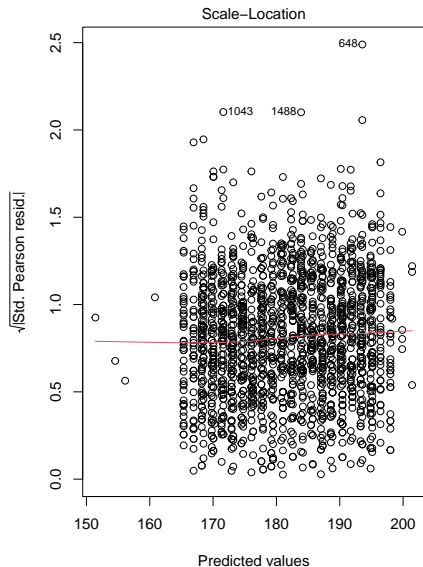
```
par(mfrow = c(1,2)); plot(glm1_results, which = c(3,5))
```



# Residuals for Model glm2\_res



# Residuals for Model glm2\_res



## Section 3

### A More Complete Weighted NHANES Analysis



# New Question, New Data

Key Source:

[https://wwwn.cdc.gov/nchs/data/tutorials/DB303\\_Fig1\\_R.R](https://wwwn.cdc.gov/nchs/data/tutorials/DB303_Fig1_R.R)

Now, we are looking at the percentage of persons aged 20 and over with depression, by age and sex, in the US in 2013-2016. Pull in data using `nhanesA...`

```
DEMO_H <- nhanes('DEMO_H', translated = FALSE) |>
  select(SEQN, RIAGENDR, RIDAGEYR, SDMVSTRA, SDMVPSU, WTMEC2YR)
DEMO_I <- nhanes('DEMO_I', translated = FALSE) |>
  select(SEQN, RIAGENDR, RIDAGEYR, SDMVSTRA, SDMVPSU, WTMEC2YR)
DEMO <- bind_rows(DEMO_H, DEMO_I)
DPQ_H <- nhanes('DPQ_H', translated = FALSE)
DPQ_I <- nhanes('DPQ_I', translated = FALSE)
DPQ <- bind_rows(DPQ_H, DPQ_I)
```

## Merge DEMO and DPQ files and create derived variables

```
dat2 <- left_join(DEMO, DPQ, by = "SEQN") |> tibble() |>
  # Set 7=Refused and 9=Don't Know To NA
  mutate(across(.cols = DPQ010:DPQ090,
    ~ ifelse(. >=7, NA, .))) %>%
  mutate(one = 1,
    PHQ9_score = rowSums(select(. , DPQ010:DPQ090)),
    Depression = ifelse(PHQ9_score >= 10, 100, 0),
    Sex = factor(RIAGENDR, labels = c("M", "F")),
    Age_group = cut(RIDAGEYR,
      breaks = c(-Inf, 19, 39, 59, Inf),
      labels = c("Under 20", "20-39", "40-59", "60+")),
    WTMEC4YR = WTMEC2YR/2,
    inAnalysis = (RIDAGEYR >= 20 & !is.na(PHQ9_score)))
  select(-starts_with("DPQ"))
```

## Define Survey Design

Here's the survey design for the overall data set:

```
NH_des_all <- svydesign(data = dat2, id = ~ SDMVPSU,  
  strata = ~ SDMVSTRA, weights = ~ WTMEC4YR, nest = TRUE)  
  
dim(NH_des_all)
```

```
[1] 20146    13
```

Here's the survey design object for the subset of interest: adults aged 20 and over with a valid PHQ-9 depression score:

```
NH_des_dat2 <- NH_des_all |> subset(inAnalysis)  
  
dim(NH_des_dat2)
```

```
[1] 9942    13
```

## Define a function to call svymean and unweighted count

```
ourSummary <- function(varformula, byformula, design){  
  # Get mean, stderr, and unweighted sample size  
  c <- svyby(varformula, byformula, design, unwtd.count )  
  p <- svyby(varformula, byformula, design, svymean )  
  outSum <- left_join(select(c,-se), p)  
  outSum  
}
```

## Estimate overall prevalence of depression

```
ourSummary(~ Depression, ~ one, NH_des_dat2)
```

	one	counts	Depression	se
1	1	9942	8.056844	0.3599894

# Estimate prevalence of depression in various strata

*## By sex*

```
ourSummary(~ Depression, ~ Sex, NH_des_dat2)
```

	Sex	counts	Depression	se
1	M	4821	5.549344	0.4293217
2	F	5121	10.427654	0.5658239

*## By age*

```
ourSummary(~ Depression, ~ Age_group, NH_des_dat2)
```

	Age_group	counts	Depression	se
1	20-39	3328	7.744613	0.5236944
2	40-59	3307	8.429826	0.6164284
3	60+	3307	7.971216	0.7797954

# Estimate prevalence of depression by Age and Sex

```
## By sex and age
```

```
ourSummary(~ Depression, ~ Sex + Age_group, NH_des_dat2)
```

	Sex	Age_group	counts	Depression	se
1	M	20-39	1654	5.513778	0.6461045
2	F	20-39	1674	10.050321	0.8036891
3	M	40-59	1556	5.222060	0.7699895
4	F	40-59	1751	11.477238	1.2011361
5	M	60+	1611	6.052782	0.8295114
6	F	60+	1696	9.579923	1.0534115

# Compare Prevalence between Male and Female

Across all age groups:

```
svytest(Depression ~ Sex, NH_des_dat2)
```

Design-based t-test

```
data: Depression ~ Sex
```

```
t = 6.8246, df = 29, p-value = 1.706e-07
```

```
alternative hypothesis: true difference in mean is not equal to 0
```

```
95 percent confidence interval:
```

```
3.416354 6.340267
```

```
sample estimates:
```

```
difference in mean
```

```
4.87831
```

# Compare Prevalence between Male and Female

In people ages 40-59:

```
svyttest(Depression ~ Sex, subset(NH_des_dat2, Age_group == "40-59"))
```

Design-based t-test

```
data: Depression ~ Sex
t = 3.8688, df = 29, p-value = 0.0005706
alternative hypothesis: true difference in mean is not equal to 0
95 percent confidence interval:
 2.948407 9.561949
sample estimates:
difference in mean
 6.255178
```



## Differences by Age Group, among Adults

```
svyttest(Depression ~ Age_group, subset(NH_des_dat2,  
                                           Age_group=="20-39" | Age_group=="40-59"))
```

Design-based t-test

```
data: Depression ~ Age_group  
t = 0.79398, df = 29, p-value = 0.4337  
alternative hypothesis: true difference in mean is not equal to 0  
95 percent confidence interval:  
-1.079836  2.450262  
sample estimates:  
difference in mean  
0.6852129
```

## Next Time?

- Linear Regression and ANOVA / ANCOVA models
- Incorporating Polynomials into our models

## Reminders

- 1 Please complete the **Minute Paper after Class 3** by noon tomorrow (Wednesday 2024-01-24)
- 2 Get started on **Lab 2**, due next Tuesday 2024-01-30 at Noon.
- 3 Continue reading **How To Be A Modern Scientist**