

poa_financial_security

Arielle Herman

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Contents

Summary of Findings	2
Data Description	2
2.1) Households that saw a reduction in income between 2019 and 2021 [12 & 13]	5
Findings (some statistically significant differences):	5
2.2) Households whose income dropped below the poverty line from 2019 to 2021 [12 & 13]	9
Findings (one statistically significant finding with caveat):	9
2.3) People who are currently receiving unemployment benefits were more likely to not face a reduced 2021 household income [16,12,13]	13
Findings (sample size too small)	13
2.4) People who were unemployed before March 2020 were more likely to have a reduced 2021 household income [14,12,13]	14
Findings (no statistically significant finding)	14
2.5) People who worked non-full-time jobs were more likely to foresee a reduced 2021 income [14,12,13]	15
Findings (no statistically significant result)	15
2.6) People who had difficulty paying bills in the past year [20]	16
Findings (some statistically significant findings)	16
2.7) People who had difficulty paying rent in the past year [20]	27
Findings (some statistically significant findings)	27
2.8) Households that were financially unstable in the past year [20]	39
Findings (some statistically significant findings)	39

2.9)Households that experienced food insecurity in the past year [20]	51
Findings (some statistically significant findings)	51
2.10)Households with children were more likely to experience food insecurity in the past year [24,20]	62
Findings (statistically significant finding)	62
2.11)Respondents who experienced a reduced income were more likely to rate government response poorly [12 &13]	63
Findings (No statistically significant result)	63
2.12)Respondents who have a low income (below median income) are more likely to experience violence [12, 13, 34]	64
Findings (statistically significant difference on 90% confidence level)	64
2.13)Respondents who have a low income (below median income) are more likely to be worried about transport while their child attends in-person school	65
Findings (No statistically significant result)	65

Summary of Findings

1. Nearly every time, sch level was negatively associated with stress, and speaking a language other than English at home or having children was positively associated with stress.
2. Black and Hispanic respondents frequently experienced more stress than white respondents.

Data Description

Data heavily skewed towards higher income brackets

```
categories <- attributes(wrangled$inc_after)$labels

wrangled %>%
  select(inc_before, inc_after) %>%
  mutate_if(is.labelled, labelled::to_character) %>%
  count(inc_before)

## # A tibble: 16 x 2
##   inc_before      n
##   <chr>      <int>
## 1 $10,000 - $19,999    79
## 2 $100,000 - $149,999  165
## 3 $150,000 - $199,999   88
## 4 $20,000 - $29,999    69
## 5 $200,000 - $299,999   76
## 6 $30,000 - $34,999    45
## 7 $300,000 or more   102
## 8 $35,000 - $39,999    24
```

```
## 9 $40,000 - $49,999      69
## 10 $50,000 - $59,999    65
## 11 $60,000 - $69,999    52
## 12 $70,000 - $79,999    61
## 13 $80,000 - $89,999    54
## 14 $90,000 - $99,999    59
## 15 less than $10,000    96
## 16 <NA>                  1
```

```
arranged <- tibble(range = names(categories)) %>%
  left_join(wrangled %>% mutate(range = labelled::to_character(inc_before)) %>%
    count(range, inc_before)) %>%
  mutate(range = str_replace_all(range, c("less than" = "$0 -", "or more" = "- $450,000+"))) %>%
  separate(col = range, into = c("min", "max"), sep = " - ", remove = FALSE) %>%
  mutate(across(min:max, ~as.double(str_replace_all(., "\\$|,|\\+", "")))) %>%

  na.omit()# come back to top bracket later
```

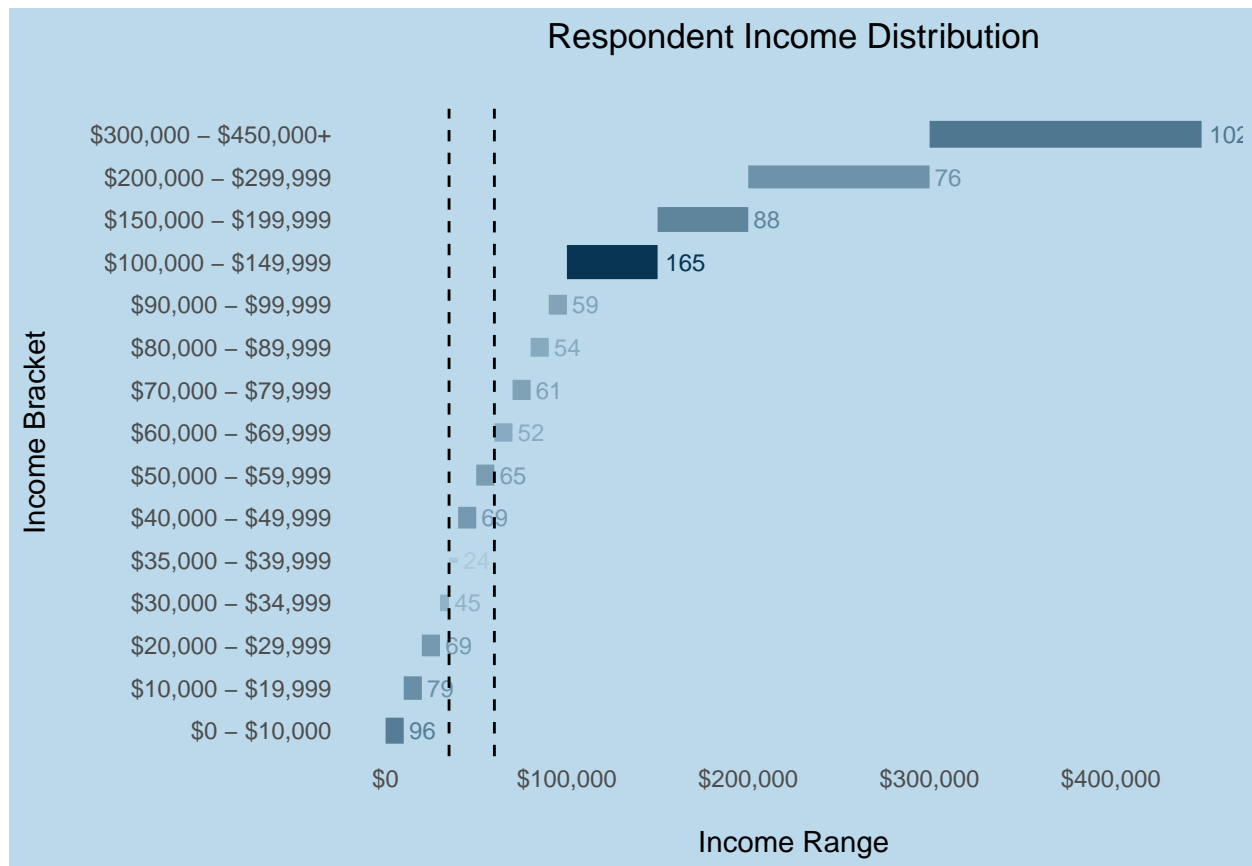
```
## Joining, by = "range"
```

```
inc_dist_plot <- arranged %>%

  ggplot(aes(y = reorder(range, max), alpha = n), show.legend = FALSE) +
  #geom_col(aes(x = max)) +
  geom_linerange(aes(xmin = min, xmax = max, size = n), color = project_pal[4], show.legend = FALSE) +
  geom_vline(xintercept = c(35000, 60000),
    labels = c("poverty line", "median income"), lty = "dashed") +
  geom_text(aes(x = max, label = n), hjust = -0.2, color = project_pal[4], size = 3, show.legend = FALSE) +
  scale_x_continuous(labels = scales::dollar) +
  #annotate("text", x = 0, y = c(poverty_line), label = c("Respondents\nBelow Poverty Line"))
  #geom_jitter(data = wrangled, aes(x = ))
  ylab("Income Bracket\n") + xlab("\nIncome Range") +
  ggtitle("Respondent Income Distribution\n")
```

```
## Warning: Ignoring unknown parameters: labels
```

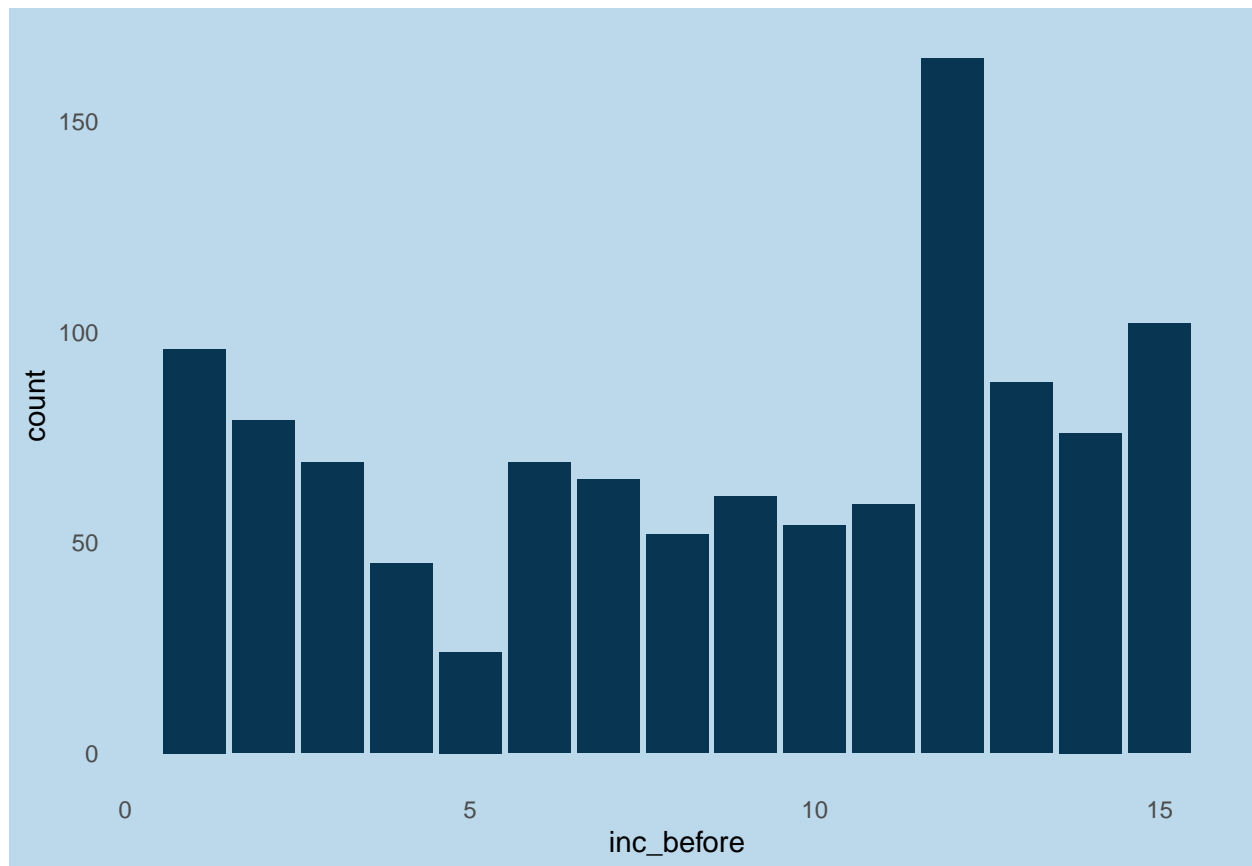
```
inc_dist_plot
```



```
ggplot(data = wrangled, aes(x = inc_before)) + geom_bar(fill = project_pal[4])
```

```
## Don't know how to automatically pick scale for object of type haven_labelled/vctrs_vctr/integer. Def
```

```
## Warning: Removed 1 rows containing non-finite values (stat_count).
```



2.1) Households that saw a reduction in income between 2019 and 2021 [12 &13]

Compare predicted 2021 income with 2019 income to find positive or negative change
 Run distribution of negative changes over population
 Run distribution by sub-demographics (a-k)
 Compare and find gaps (test unequal proportions)

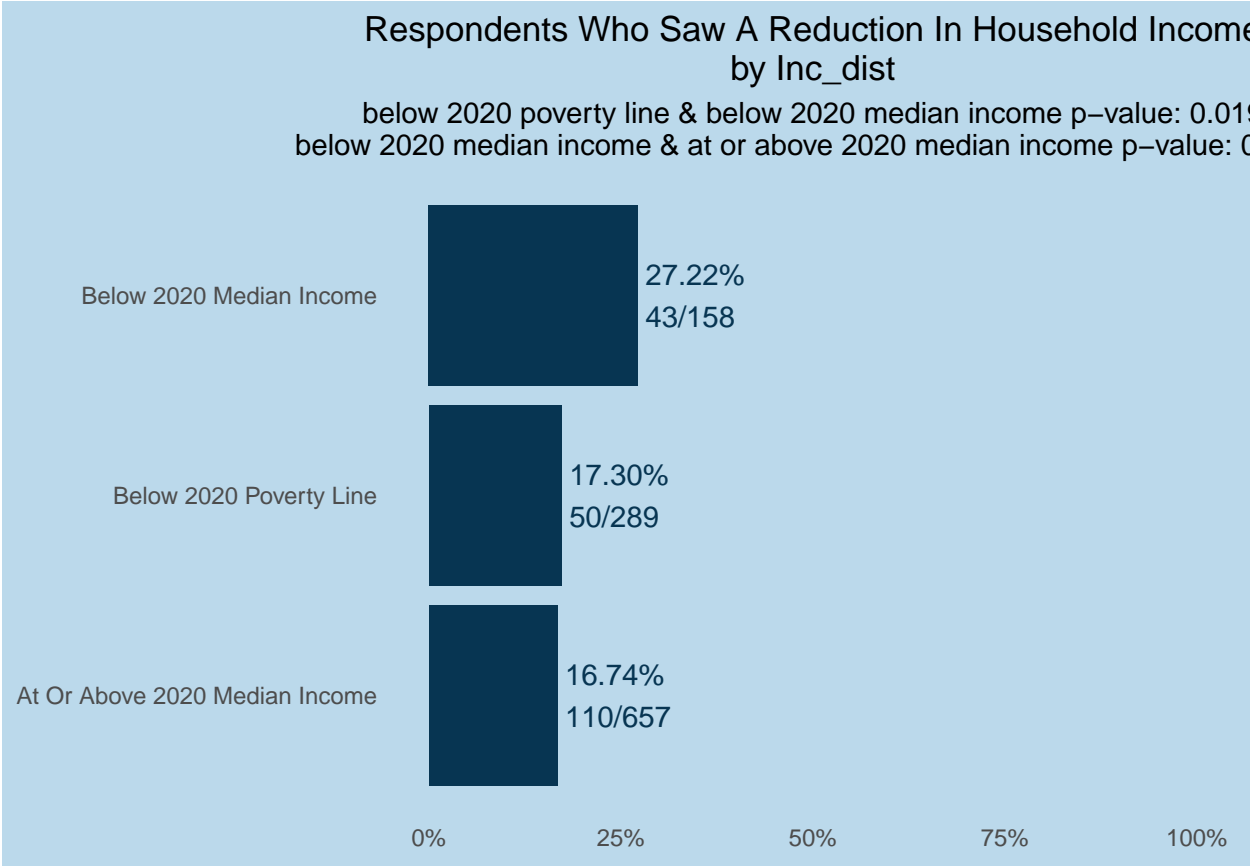
Findings (some statistically significant differences):

The greatest proportion of people to see a reduction in income throughout the pandemic by

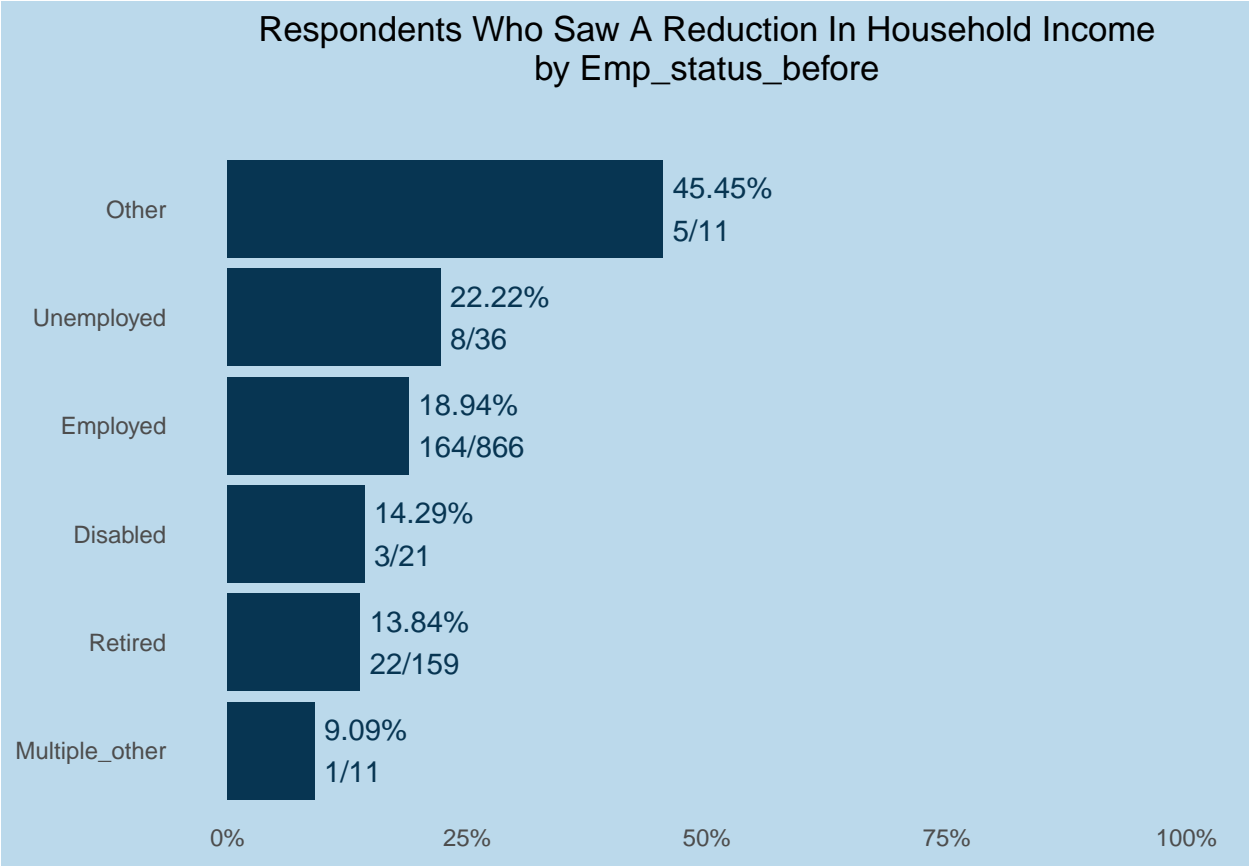
- **employment status** were unemployed after the pandemic
- **income distribution** were in between the poverty line and the median income level

```
plots2.1 <- make_plots(df = wrangled, by_vars = demographics, hyp_var = "inc_neg", min = 5,
  title = "Respondents who saw a reduction in household income", show = "yes")[c("inc_dist", "
plots2.1
```

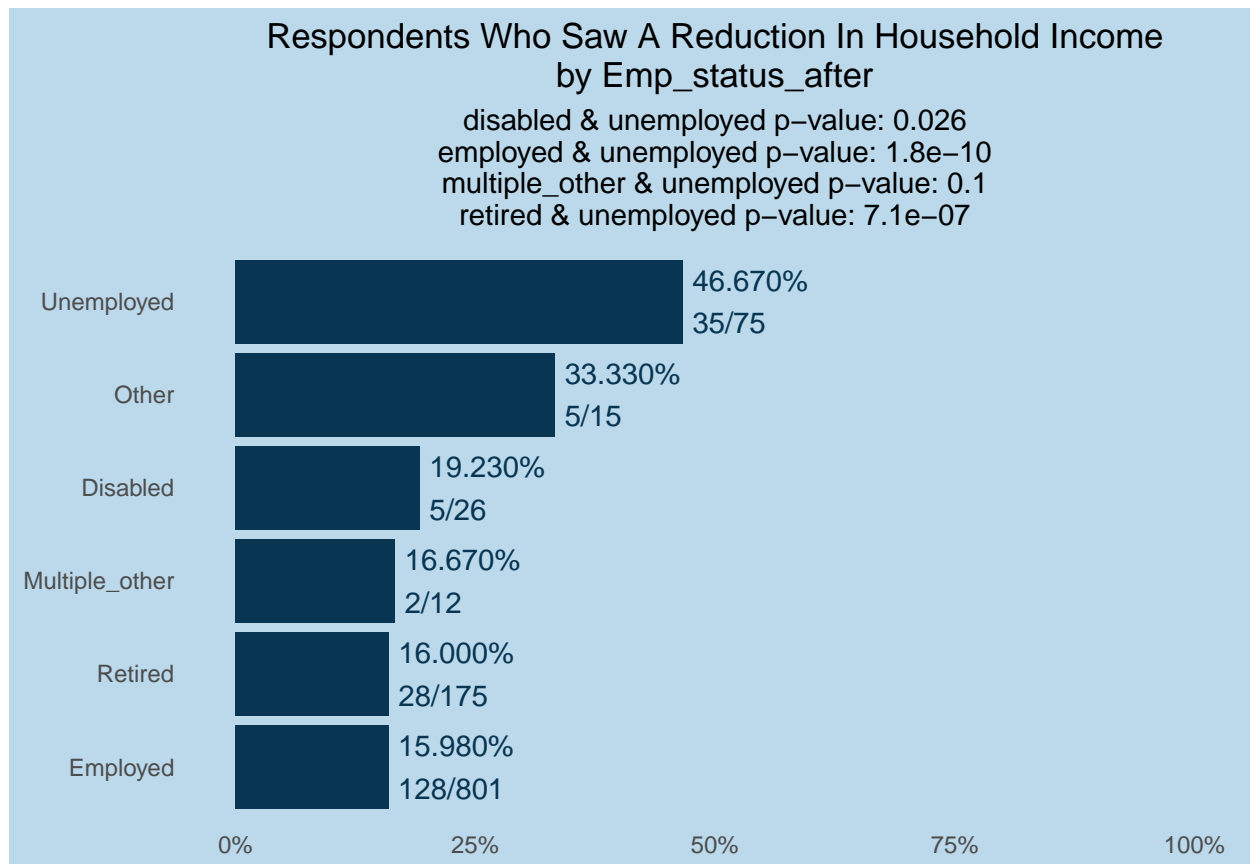
```
## $inc_dist
```



```
##  
## $emp_status_before
```



\$emp_status_after



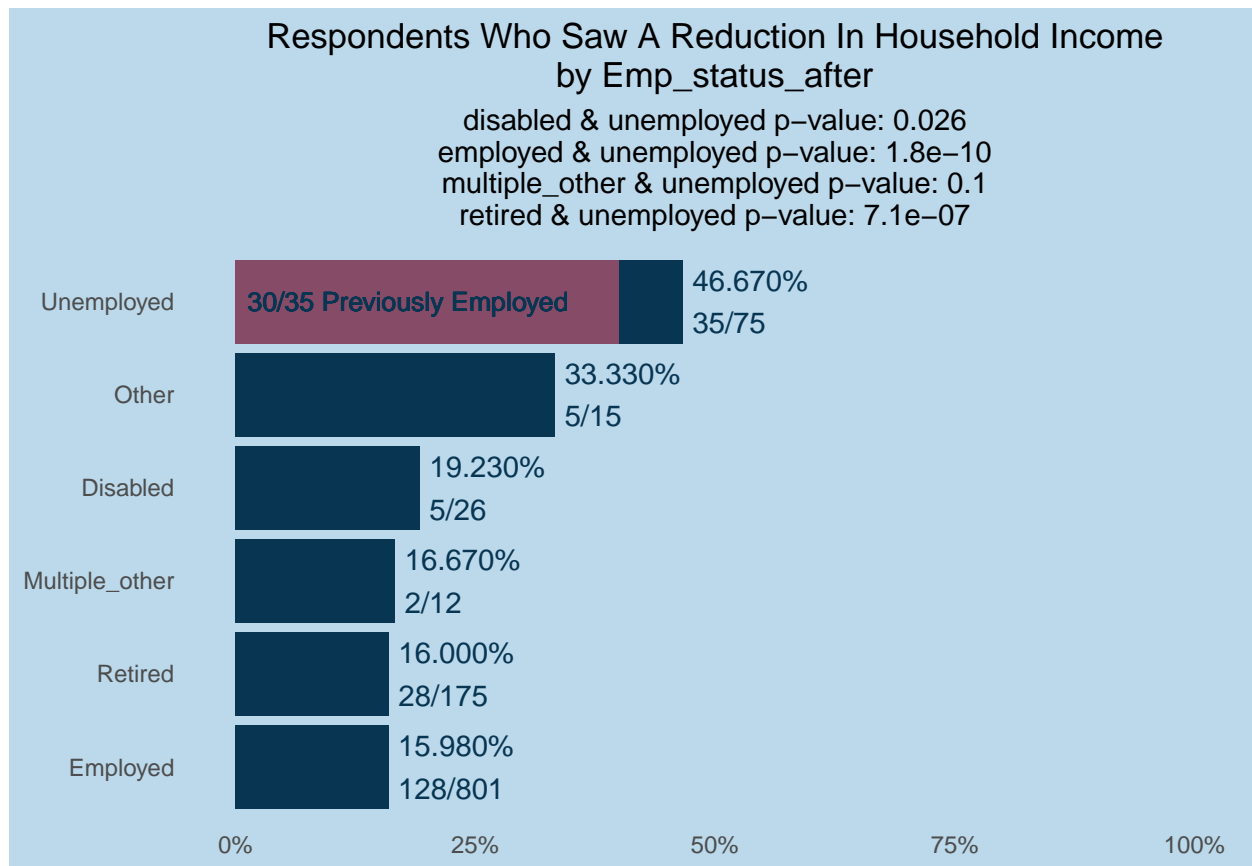
This two plots grouped by employment status before and after the start of the pandemic suggests that the majority of respondents who experienced a reduction in income, were originally employed. We can confirm this with the below graph.

```
(became_unemp <- wrangled %>% filter(str_detect(emp_status_after, "unemp")) %>%
  #group_by(emp_status_before) %>%
  #group_by(inc_neg == 1) %>%
  summarize(n = sum(!str_detect(emp_status_before, "unemp") & inc_neg == 1, na.rm = TRUE),
    n_n = sum(inc_neg == 1, na.rm = TRUE),
    denom = sum(!is.na(!str_detect(emp_status_before, "unemp"))),
    prop = n/denom))
```

```
## # A tibble: 1 x 4
##       n   n_n denom  prop
##   <int> <int> <int> <dbl>
## 1    30    35    75   0.4
```

```
plots2.1$emp_status_after +
  geom_col(data = tibble(emp_status_after = "Unemployed", prop = became_unemp$prop),
    fill = project_pal[3]) +
  geom_text(aes(x = .18, y = "Unemployed"), size = 3.5, label = glue::glue("{paste(became_unemp[c('n', 'n_n'), 1]
    collapse = '/')} Previously Employed"),
    color = project_pal[4],
    fill = project_pal[3])
```

```
## Warning: Ignoring unknown parameters: fill
```

2.2) Households whose income dropped below the poverty line from 2019 to 2021 [12 & 13]

Run distribution over population Run distribution by sub-demographics (a-k) and type of previous employment [13] Compare and find gaps (test unequal proportions)

Findings (one statistically significant finding with caveat):

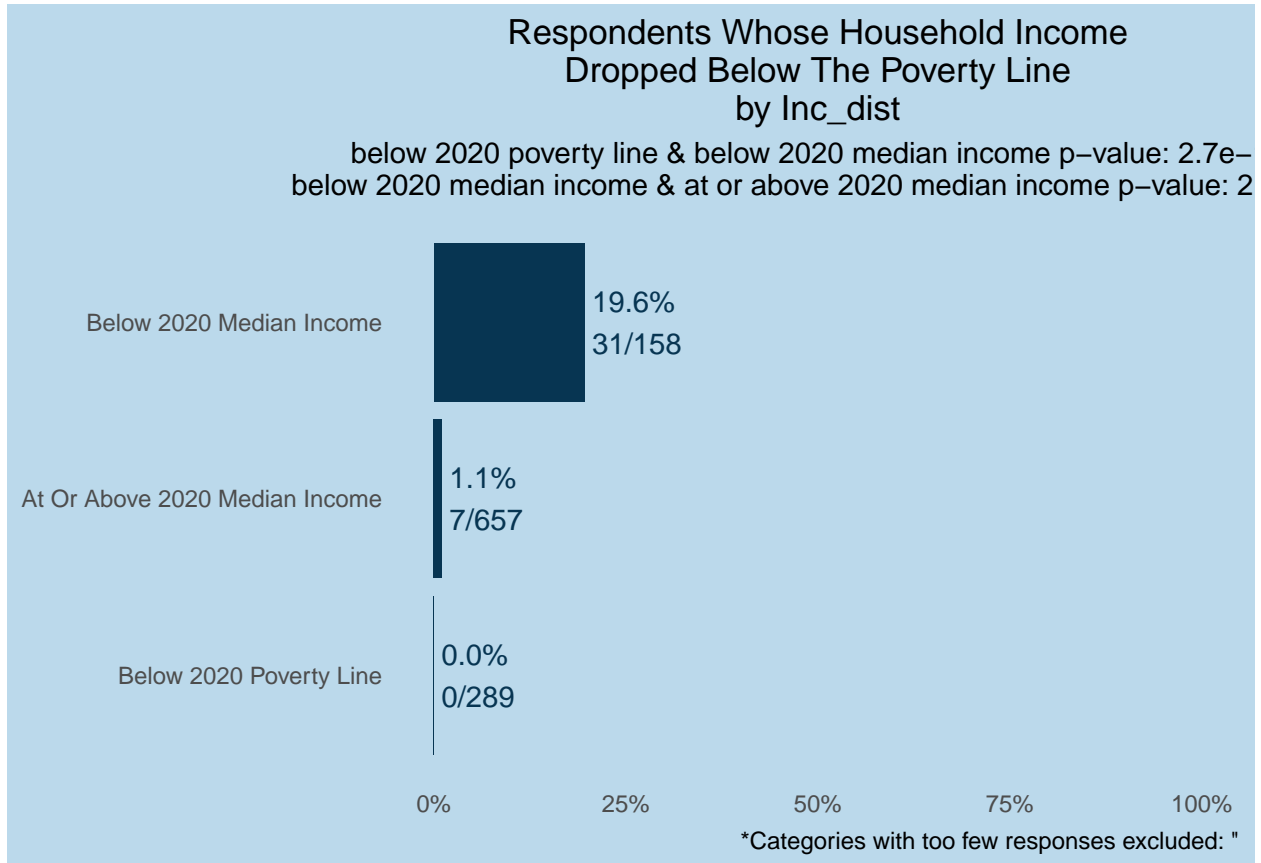
20% of respondents starting below the median income level but above the poverty line, ended up below the poverty line after the pandemic. This may result simply because this range is the smallest of the three, and because it is much closer to the poverty line. (See first plot).

```
wrangled %>% count(inc_drop_pov, inc_dist) %>%
  mutate_if(is.labelled, labelled::to_character) %>% na.omit
```

```
## # A tibble: 5 x 3
##   inc_drop_pov      inc_dist      n
##   <chr>          <chr>    <int>
## 1 income did not drop below poverty line below 2020 poverty line    289
## 2 income did not drop below poverty line below 2020 median income    127
## 3 income did not drop below poverty line at or above 2020 median income    650
## 4 income dropped below poverty line below 2020 median income     31
## 5 income dropped below poverty line at or above 2020 median income      7
```

```
make_plots(wrangled, by_vars = demographics, hyp_var = "inc_drop_pov",
           min = 7,
           title = "Respondents whose household income\ndropped below the poverty line", show = TRUE)[".
```

```
## $inc_dist
```



Likely, the few respondents who dropped below the poverty line who started above the median income bracket were originally close to the median income level.

```
arranged
```

```
## # A tibble: 15 x 5
##   range                min    max      inc_before    n
##   <chr>             <dbl> <dbl>      <int+lbl> <int>
## 1 $0 - $10,000         0 10000  1 [less than $10,000]    96
## 2 $10,000 - $19,999 10000 19999  2 [$10,000 - $19,999]    79
## 3 $20,000 - $29,999 20000 29999  3 [$20,000 - $29,999]    69
## 4 $30,000 - $34,999 30000 34999  4 [$30,000 - $34,999]    45
## 5 $35,000 - $39,999 35000 39999  5 [$35,000 - $39,999]    24
## 6 $40,000 - $49,999 40000 49999  6 [$40,000 - $49,999]    69
## 7 $50,000 - $59,999 50000 59999  7 [$50,000 - $59,999]    65
## 8 $60,000 - $69,999 60000 69999  8 [$60,000 - $69,999]    52
## 9 $70,000 - $79,999 70000 79999  9 [$70,000 - $79,999]    61
## 10 $80,000 - $89,999 80000 89999 10 [$80,000 - $89,999]    54
```

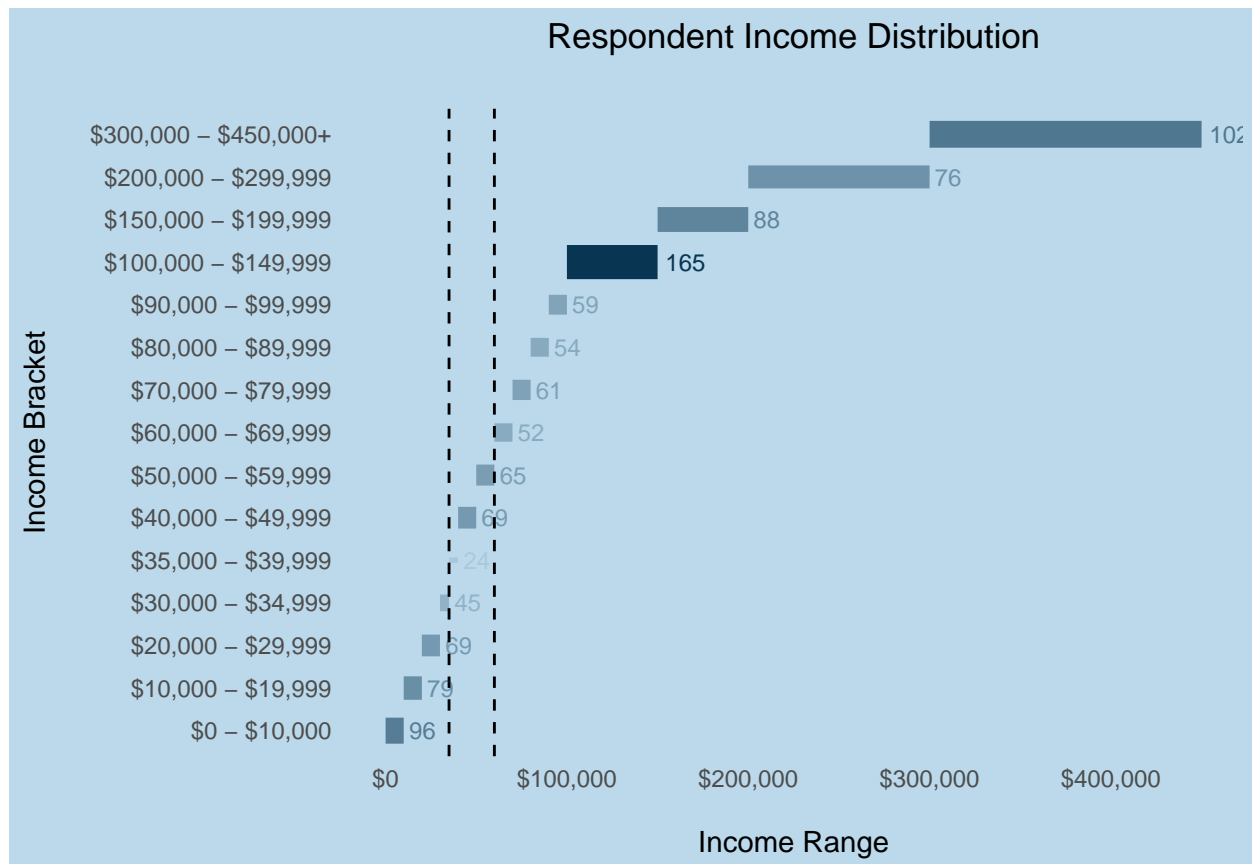
```
## 11 $90,000 - $99,999      90000  99999 11 [$90,000 - $99,999]      59
## 12 $100,000 - $149,999  100000 149999 12 [$100,000 - $149,999]    165
## 13 $150,000 - $199,999  150000 199999 13 [$150,000 - $199,999]    88
## 14 $200,000 - $299,999  200000 299999 14 [$200,000 - $299,999]    76
## 15 $300,000 - $450,000+ 300000 450000 15 [$300,000 or more]     102
```

```
counted <-
  wrangled %>% filter(inc_dist == 3, inc_drop_pov == 1) %>% count(inc_before) %>% rename(dropped = n)

tibble(categories, names(categories))
```

```
## # A tibble: 15 x 2
##   categories 'names(categories)'
##   <int> <chr>
## 1      1 less than $10,000
## 2      2 $10,000 - $19,999
## 3      3 $20,000 - $29,999
## 4      4 $30,000 - $34,999
## 5      5 $35,000 - $39,999
## 6      6 $40,000 - $49,999
## 7      7 $50,000 - $59,999
## 8      8 $60,000 - $69,999
## 9      9 $70,000 - $79,999
## 10     10 $80,000 - $89,999
## 11     11 $90,000 - $99,999
## 12     12 $100,000 - $149,999
## 13     13 $150,000 - $199,999
## 14     14 $200,000 - $299,999
## 15     15 $300,000 or more
```

```
inc_dist_plot #+
```



```
# geom_point(data = arranged %>% right_join(counted) %>% mutate(mean = mean(min, max, na.rm = TRUE)),
#           aes(x = mean), alpha = 1, pch = 21, color = "red")
```

```
wrangled %>% filter(emp_after_un == 1) %>%
  count(emp_after)
```

```
## # A tibble: 10 x 2
##   emp_after      n
##   <chr>      <int>
## 1 disabled;unemployed      2
## 2 disabled;unemployed;other      1
## 3 freelance or consultant;small business owner;unemployed      1
## 4 gig worker (uber, lyft, instacart, etc.);homemaker;unemployed      1
## 5 homemaker;disabled;unemployed      1
## 6 homemaker;unemployed      3
## 7 student;unemployed      1
## 8 unemployed      63
## 9 work full-time;unemployed      1
## 10 work part-time;unemployed      1
```

Therefore, we can look for any parallel shifts in the top bracket of the variable **inc_dist** to below the median income level. However, this change is not paralleled by a similar percentage decrease in household income of respondents starting above the median income to below the median. Only 4% of respondents above the median income level dropped below it after the pandemic.

```
wrangled %>% filter(inc_dist == 3) %>%
  summarize(prop = signif(mean(inc_drop_med, na.rm = TRUE), 2),
            n = sum(inc_drop_med, na.rm = TRUE),
            denom = sum(!is.na(inc_drop_med), na.rm = TRUE))
```

```
## # A tibble: 1 x 3
##   prop      n denom
##   <dbl> <int> <int>
## 1 0.044    29   657
```

Still, 17% of the higher third of the income distribution variable did experience a negative change in income. In order to better understand this statistic, it would be necessary to identify how much their income levels dropped.

```
wrangled %>% filter(inc_dist == 3) %>%
  summarize(prop = signif(mean(inc_neg, na.rm = TRUE), 2),
            n = sum(inc_neg, na.rm = TRUE),
            denom = sum(!is.na(inc_neg), na.rm = TRUE))
```

```
## # A tibble: 1 x 3
##   prop      n denom
##   <dbl> <int> <int>
## 1 0.17    110   657
```

2.3) People who are currently receiving unemployment benefits were more likely to not face a reduced 2021 household income [16,12,13]

Find respondents who indicated they are currently receiving unemployment benefits [16] Find proportion of subset that have a higher or equivalent income in 2021 than they reported in 2019 [12 & 13] Compare predicted 2021 income with 2019 income to find positive or negative change Find proportion not in subset that predicted a higher or equivalent income in 2021 than they reported in 2019 and compare (test unequal proportions)

Findings (sample size too small)

There were not enough respondents in this category to meaningfully analyze this hypothesis. We would have needed at least 5 successes.

```
## # A tibble: 5 x 2
##   unemp_ben      n
##   <chr>      <int>
## 1 yes          10
## 2 no, because they expired      28
## 3 no, but i tried to apply for benefits    11
## 4 no, but i did not try to apply for benefits  48
## 5 <NA>      1008
```

```
## # A tibble: 2 x 2
##               inc_neg      n
##             <int+lbl> <int>
## 1 0 [neutral or positive income change]      8
## 2 1 [negative income change]                2
```

2.4) People who were unemployed before March 2020 were more likely to have a reduced 2021 household income [14,12,13]

Find respondents who indicated were unemployed before March 2020 [14] Find proportion of subset that reported a higher or equivalent income in 2021 than they reported in 2019 [12 & 13] Compare predicted 2021 income with 2019 income to find positive or negative change Find proportion not in subset that predicted a higher or equivalent income in 2021 than they reported in 2019 and compare (test unequal proportions)

Findings (no statistically significant finding)

There was no statistically significant finding. However, it is important to note that the sample size was quite small. Only 8 unemployed people recorded a negative income change throughout the pandemic.

```
sum(wrangled$emp_before_un)
```

```
## [1] 36
```

```
mean(wrangled$emp_before_un)
```

```
## [1] 0.03257919
```

```
wrangled %>% count(emp_before_un, inc_neg) %>% mutate_if(is.labelled, labelled::to_character) %>% na.omit()
```

```
## # A tibble: 4 x 3
##   emp_before_un inc_neg      n
##   <chr>         <chr>    <int>
## 1 not unemployed neutral or positive income change 873
## 2 not unemployed negative income change      195
## 3 unemployed   neutral or positive income change      28
## 4 unemployed   negative income change           8
```

```
make_plots(wrangled, by_vars = "emp_before_un", hyp_var = "inc_neg",
            title = "Proportion of Respondents to experience\nan Adverse Income Change")
```

```
## $emp_before_un
## NULL
```

2.5) People who worked non-full-time jobs were more likely to foresee a reduced 2021 income [14,12,13]

Find respondents who indicated they work a not full-time job in 2019, 2021 (run both) [14] Not full-time job == work part-time, freelance or consultant, gig worker, small business owner Find proportion of subset that stated a higher or equivalent income in 2021 than they reported in 2019 [12 &13] Compare 2021 income with 2019 income to find positive or negative change Find proportion of full-time workers that have a higher or equivalent income in 2021 than they reported in 2019 and compare (test unequal proportions)

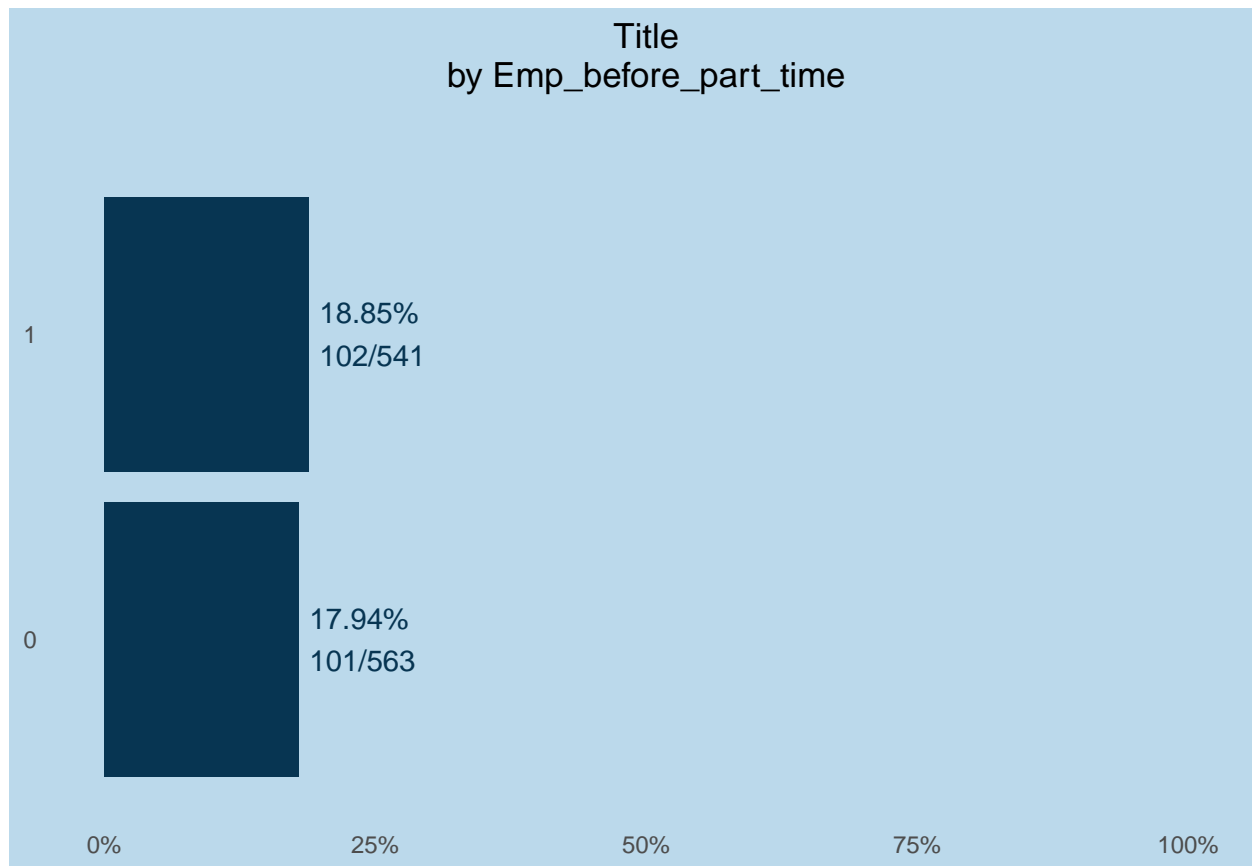
Findings (no statistically significant result)

```
wrangled %>% filter(emp_before_part_time == 1) %>% count(emp_before)
```

```
## # A tibble: 47 x 2
##   emp_before      n
##   <chr>      <int>
## 1 disabled      21
## 2 disabled;other    1
## 3 disabled;unemployed  3
## 4 freelance or consultant 58
## 5 freelance or consultant;disabled    1
## 6 freelance or consultant;gig worker (uber, lyft, instacart, etc.) 1
## 7 freelance or consultant;homemaker;retired    1
## 8 freelance or consultant;other    2
## 9 freelance or consultant;retired    4
## 10 freelance or consultant;small business owner    7
## # ... with 37 more rows
```

```
make_plots(df = wrangled, by_vars = "emp_before_part_time", hyp_var = "inc_neg", show = "yes")
```

```
## $emp_before_part_time
```



2.6) People who had difficulty paying bills in the past year [20]

Run distribution over population Run distribution by sub-demographics (a-k) Compare and find gaps (test unequal proportions)

Findings (some statistically significant findings)

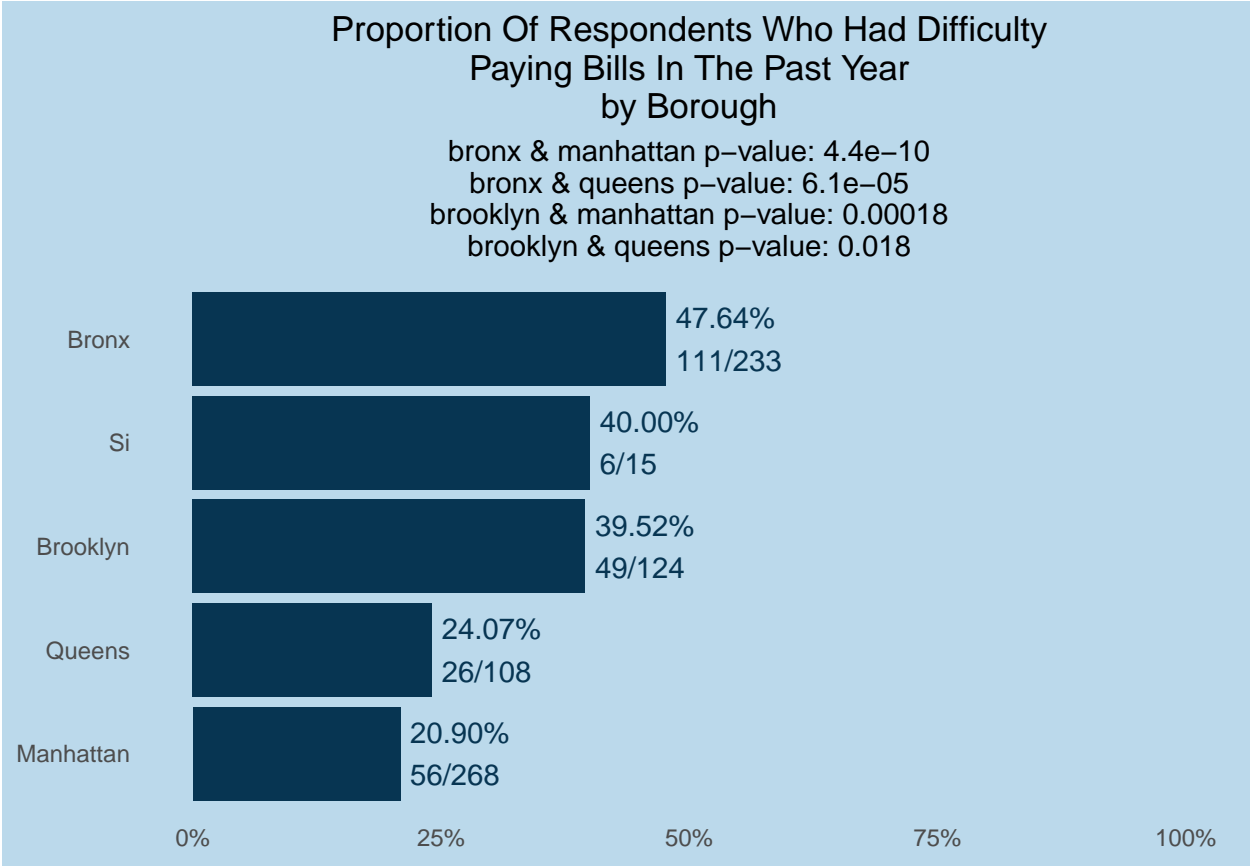
- there are many demographics that have statistically significant differences in proportions, which mostly conform to expectations (e.g. **race_census**, **not_eng**, **sch_level_cat**, **hh_ch_0_17_bi**, **emp_status** before and after)
- notably, households with seniors and elderly respondents appeared to have less difficulty paying their bills

```
mean(wrangled$diff_bill, na.rm = TRUE)
```

```
## [1] 0.3315508
```

```
make_plots(df = wrangled, demographics, "diff_bill", min = 10, title = "Proportion of Respondents who h
```

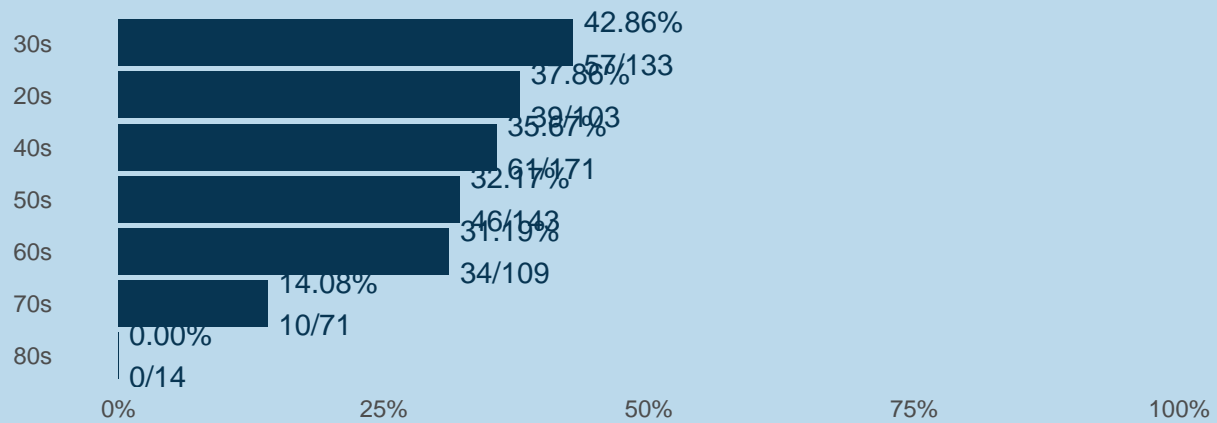
```
## $borough
```

\$decade

Proportion Of Respondents Who Had Difficulty Paying Bills In The Past Year by Decade

20s & 70s p-value: 0.0011
30s & 50s p-value: 0.087
30s & 60s p-value: 0.084
30s & 70s p-value: 6e-05
30s & 80s p-value: 0.0045
40s & 70s p-value: 0.0014
50s & 70s p-value: 0.0076
60s & 70s p-value: 0.015



*Categories with too few responses excluded: "

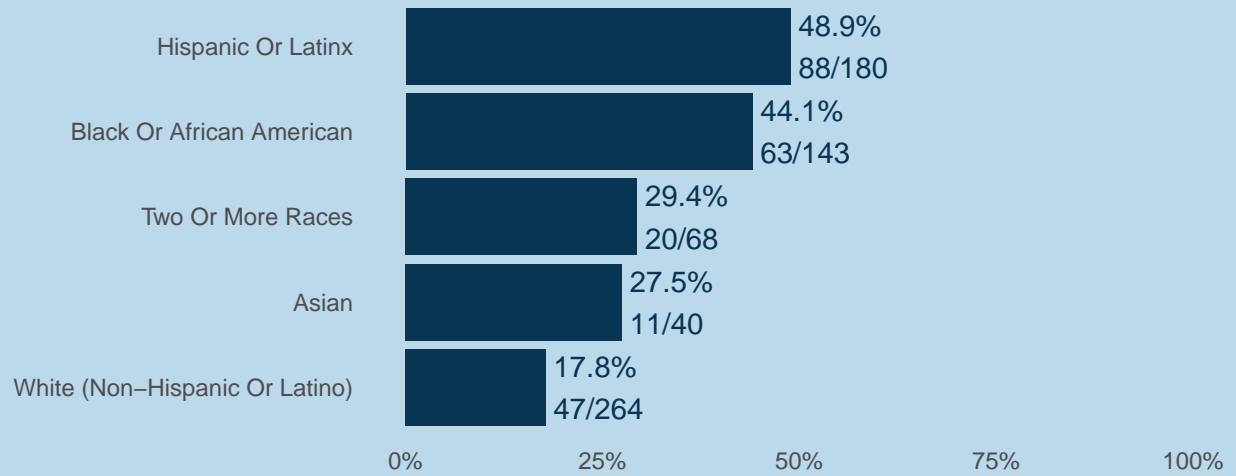
```

##
## $gen
## NULL
##
## $race_census

```

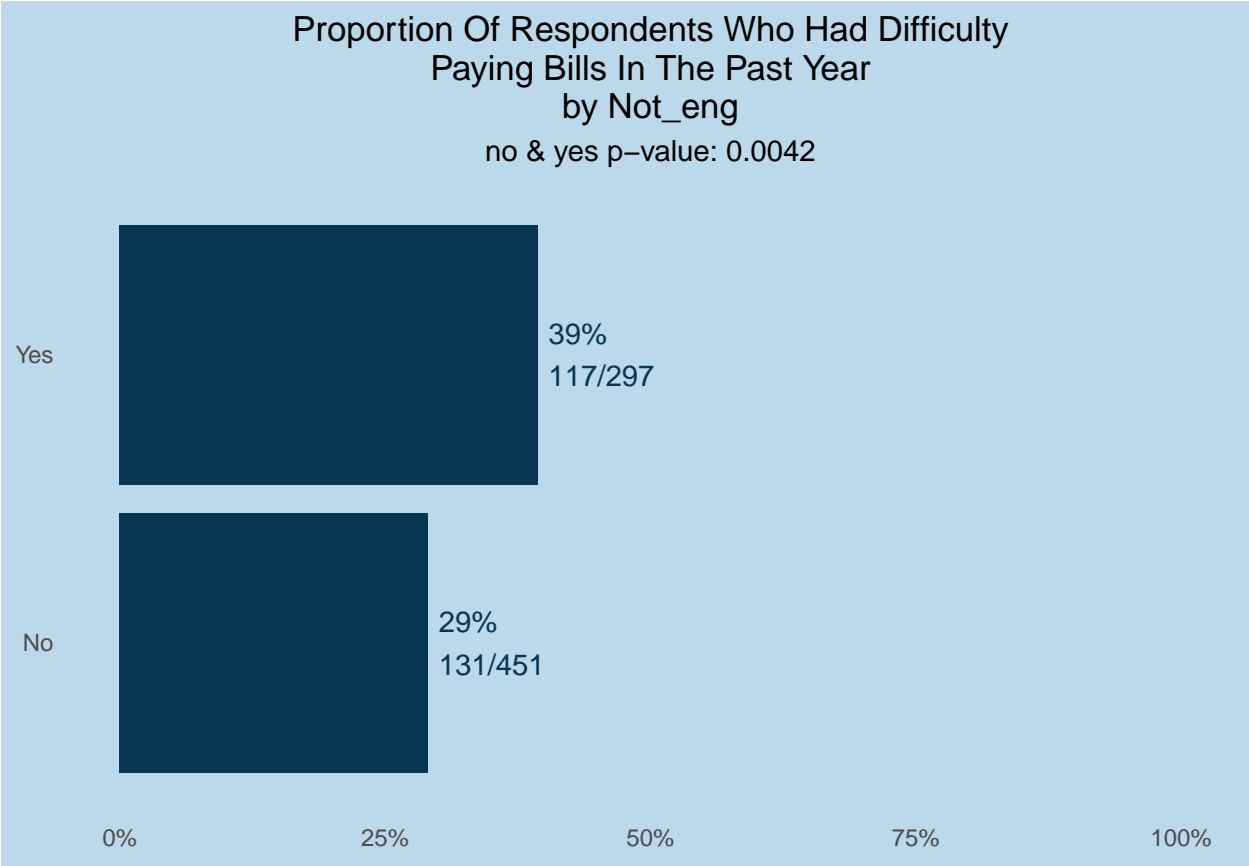
Proportion Of Respondents Who Had Difficulty Paying Bills In The Past Year by Race_census

asian & black or african american p-value: 0.088
 asian & hispanic or latinx p-value: 0.022
 black or african american & two or more races p-value: 0.06
 black or african american & white (non-hispanic or latino) p-value: 2.5e-
 hispanic or latinx & two or more races p-value: 0.0089
 hispanic or latinx & white (non-hispanic or latino) p-value: 5.7e-12
 two or more races & white (non-hispanic or latino) p-value: 0.05



##

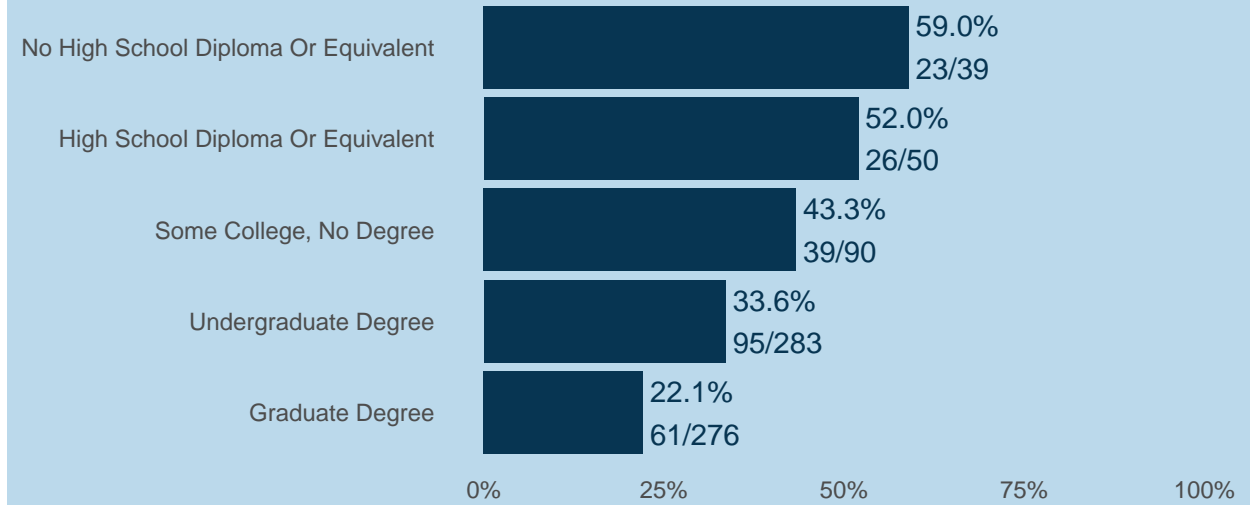
\$not_eng



```
##  
## $sch_level_cat
```

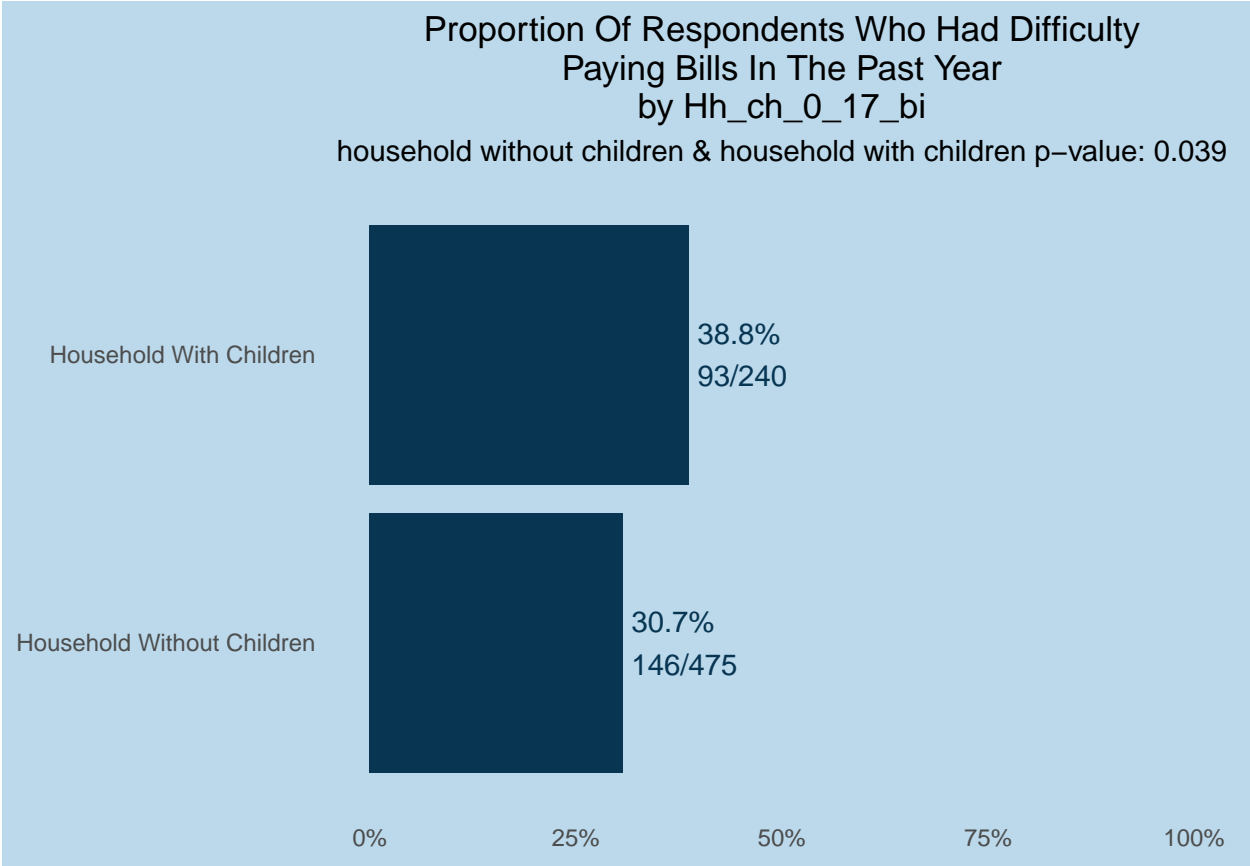
Proportion Of Respondents Who Had Difficulty Paying Bills In The Past Year by Sch_level_cat

graduate degree & high school diploma or equivalent p-value: 2.4e
graduate degree & no high school diploma or equivalent p-value: 2.9
graduate degree & some college, no degree p-value: 0.00015
graduate degree & undergraduate degree p-value: 0.0034
high school diploma or equivalent & undergraduate degree p-value: (
no high school diploma or equivalent & undergraduate degree p-value: (

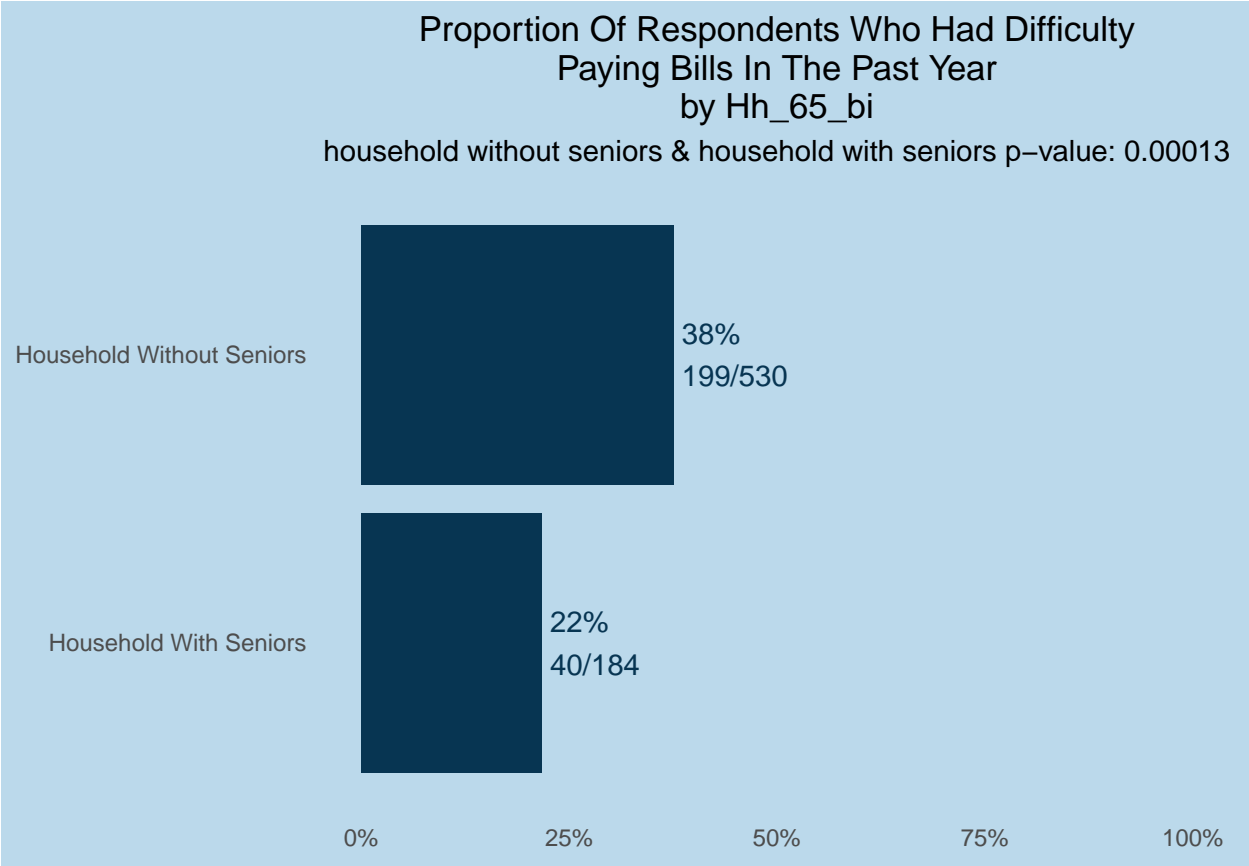


##

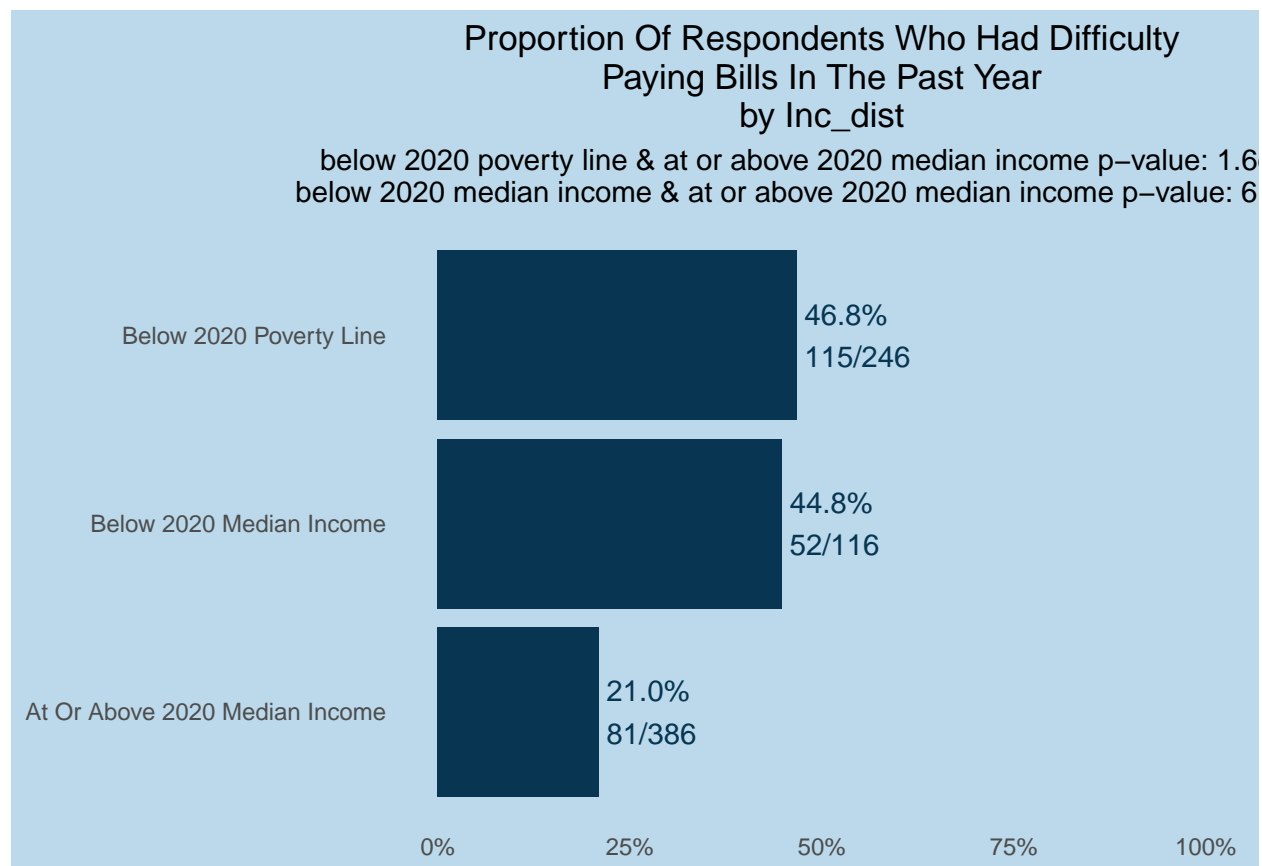
\$hh_ch_0_17_bi



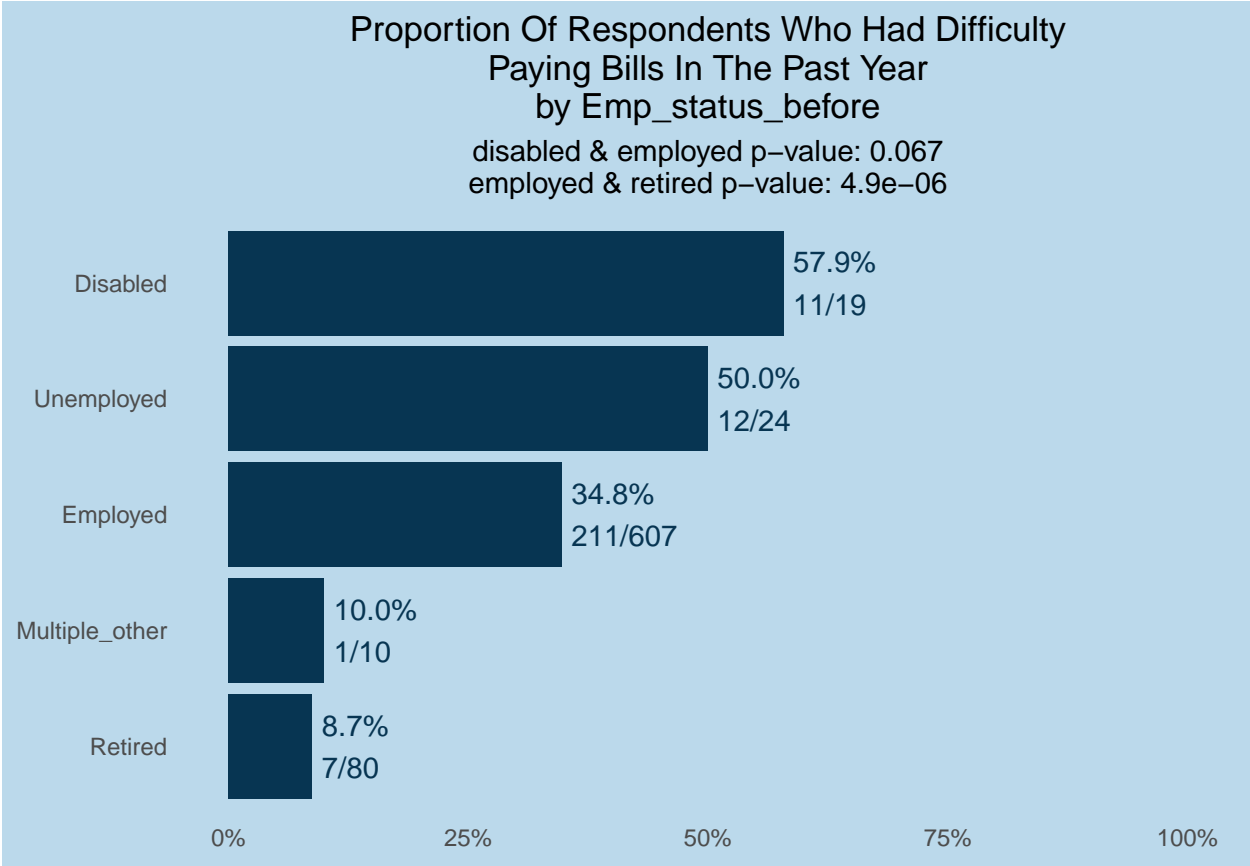
\$hh_65_bi



\$inc_dist



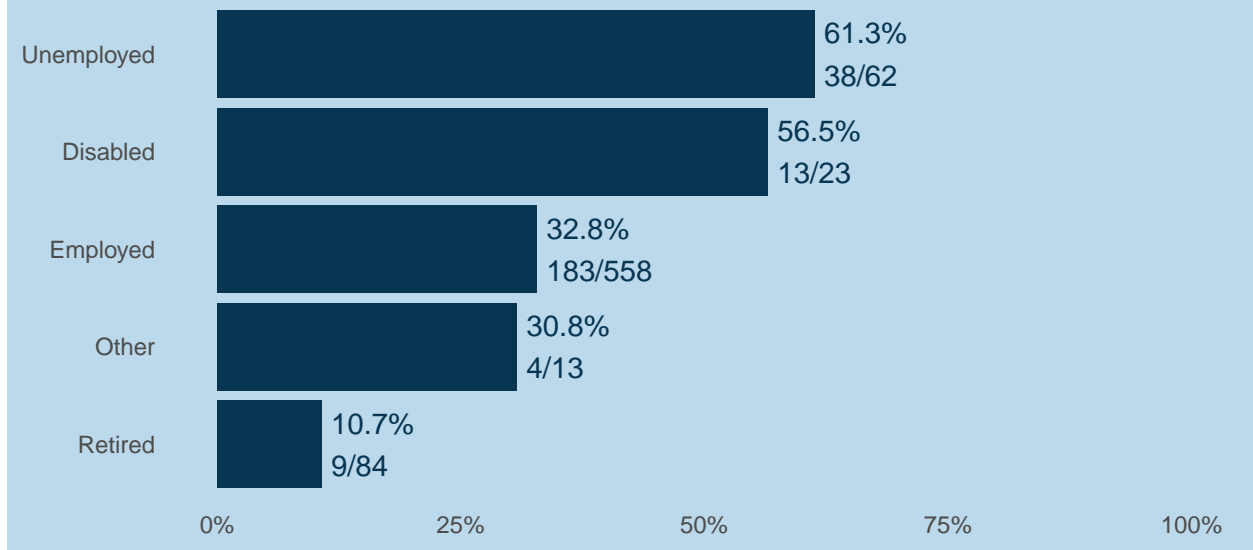
```
##  
## $emp_status_before
```

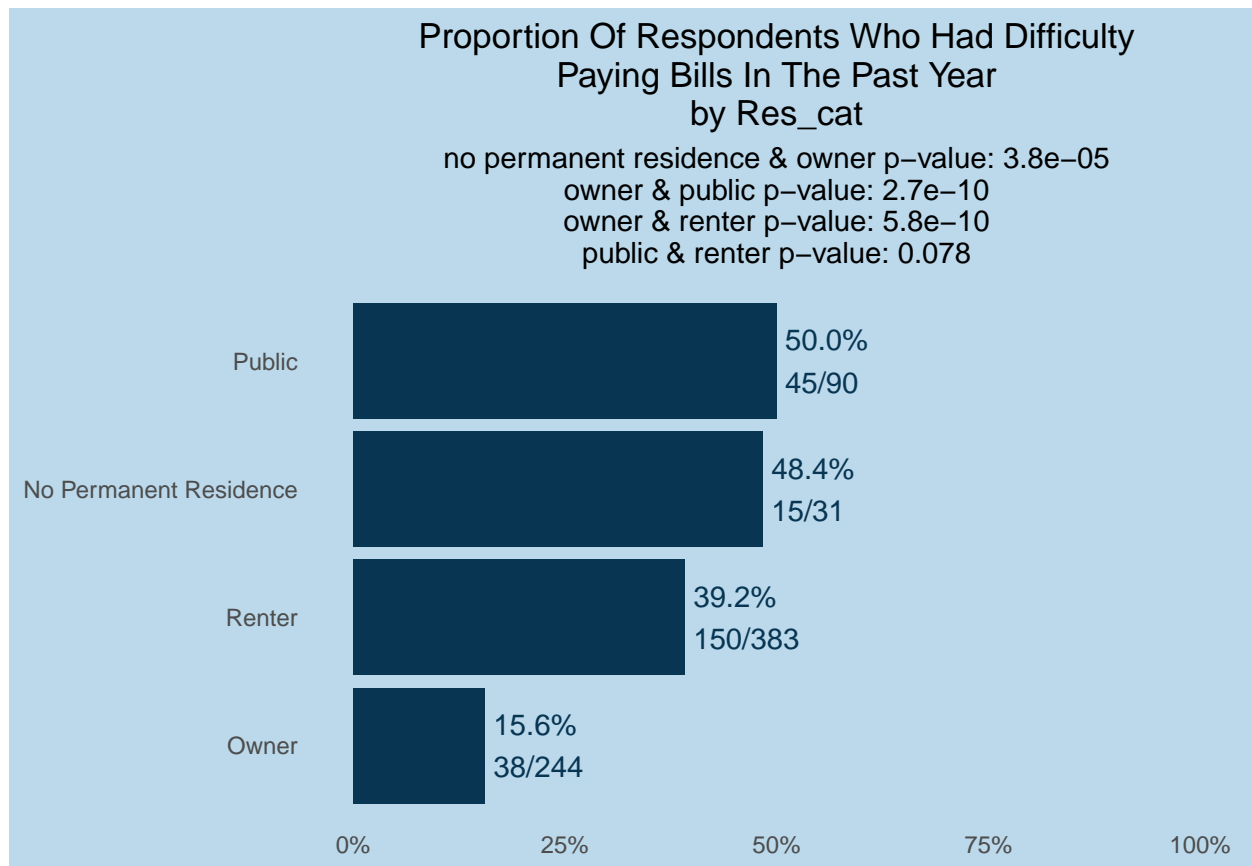
\$emp_status_after

Proportion Of Respondents Who Had Difficulty Paying Bills In The Past Year by Emp_status_after

disabled & employed p-value: 0.033
employed & retired p-value: 6.5e-05
employed & unemployed p-value: 1.7e-05
other & unemployed p-value: 0.088
retired & unemployed p-value: 3.3e-10



\$res_cat



2.7) People who had difficulty paying rent in the past year [20]

Run distribution over population Run distribution by sub-demographics (a-k) Compare and find gaps (test unequal proportions)

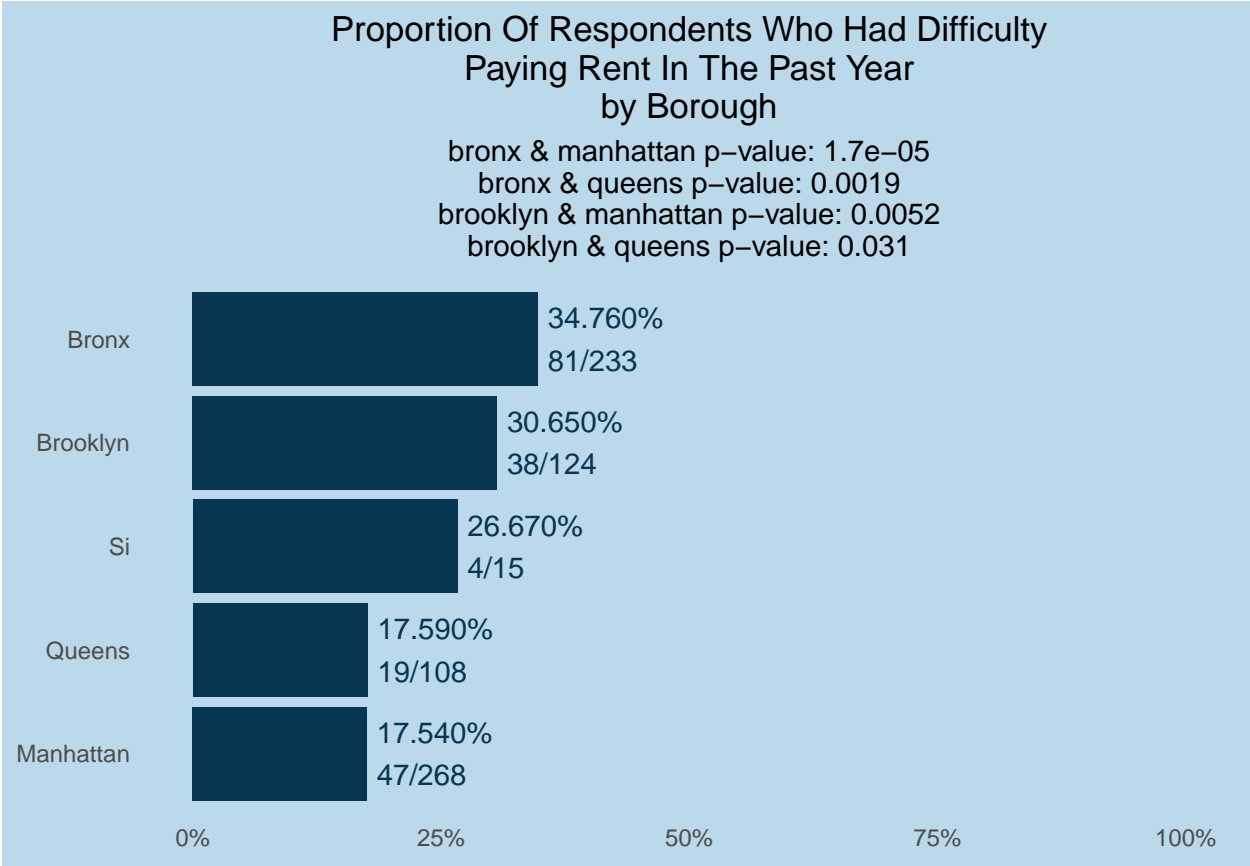
Findings (some statistically significant findings)

```
mean(wrangled$diff_rent, na.rm = TRUE)
```

```
## [1] 0.2526738
```

```
make_plots(df = wrangled, demographics, "diff_rent", min = 10, title = "proportion of respondents who h
```

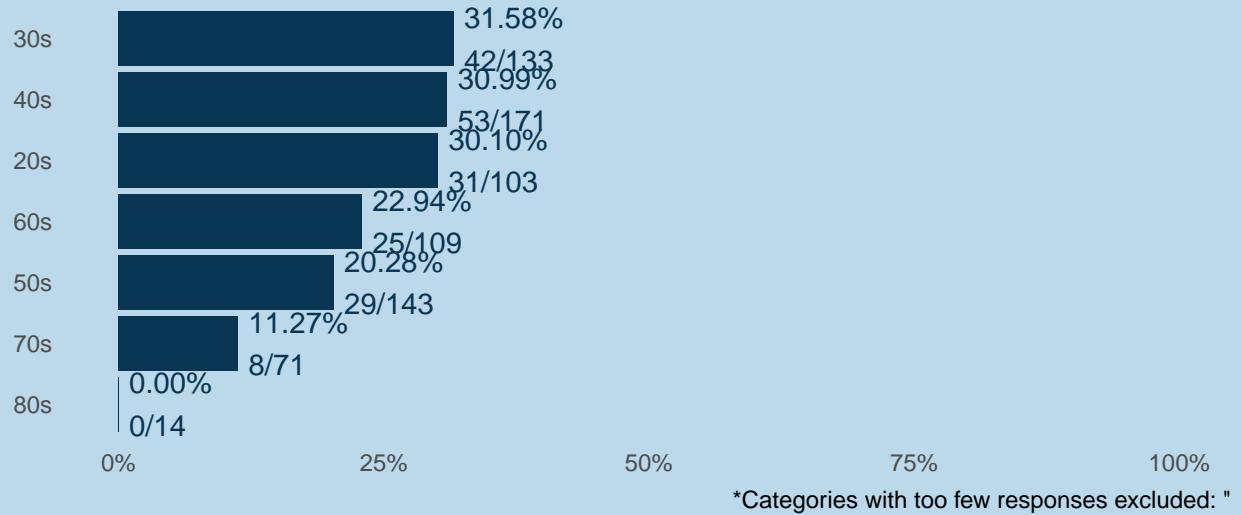
```
## $borough
```



\$decade

Proportion Of Respondents Who Had Difficulty Paying Rent In The Past Year by Decade

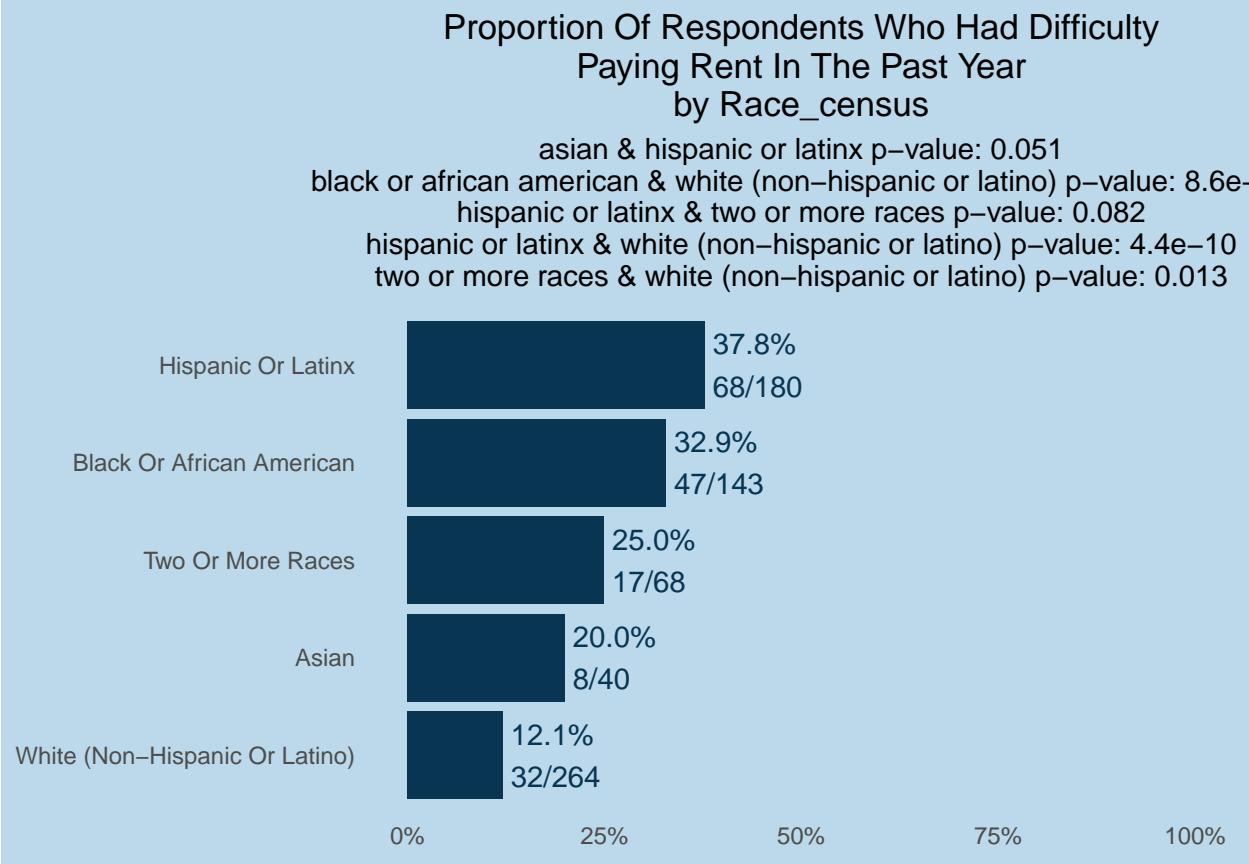
20s & 70s p-value: 0.0061
30s & 50s p-value: 0.045
30s & 70s p-value: 0.0024
40s & 50s p-value: 0.043
40s & 70s p-value: 0.0022
60s & 70s p-value: 0.075



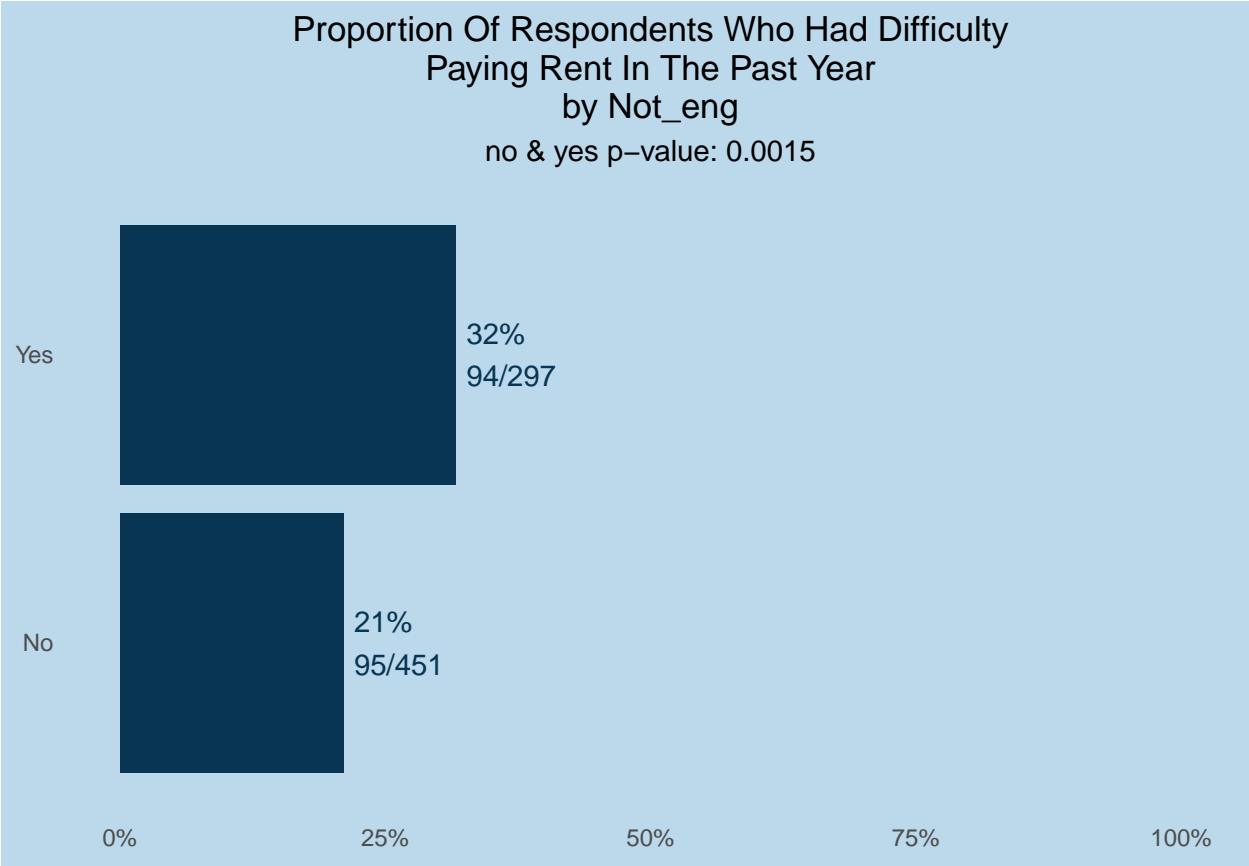
```

##
## $gen
## NULL
##
## $race_census

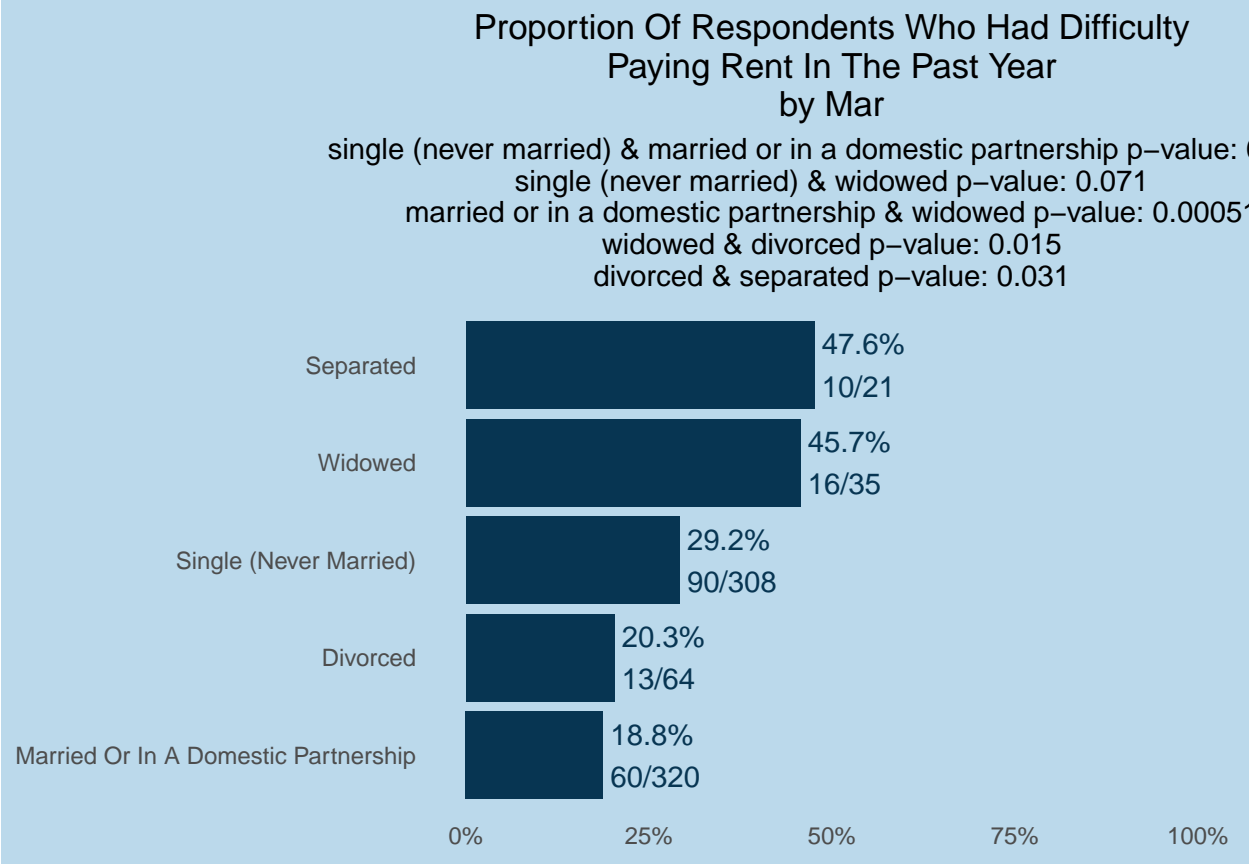
```



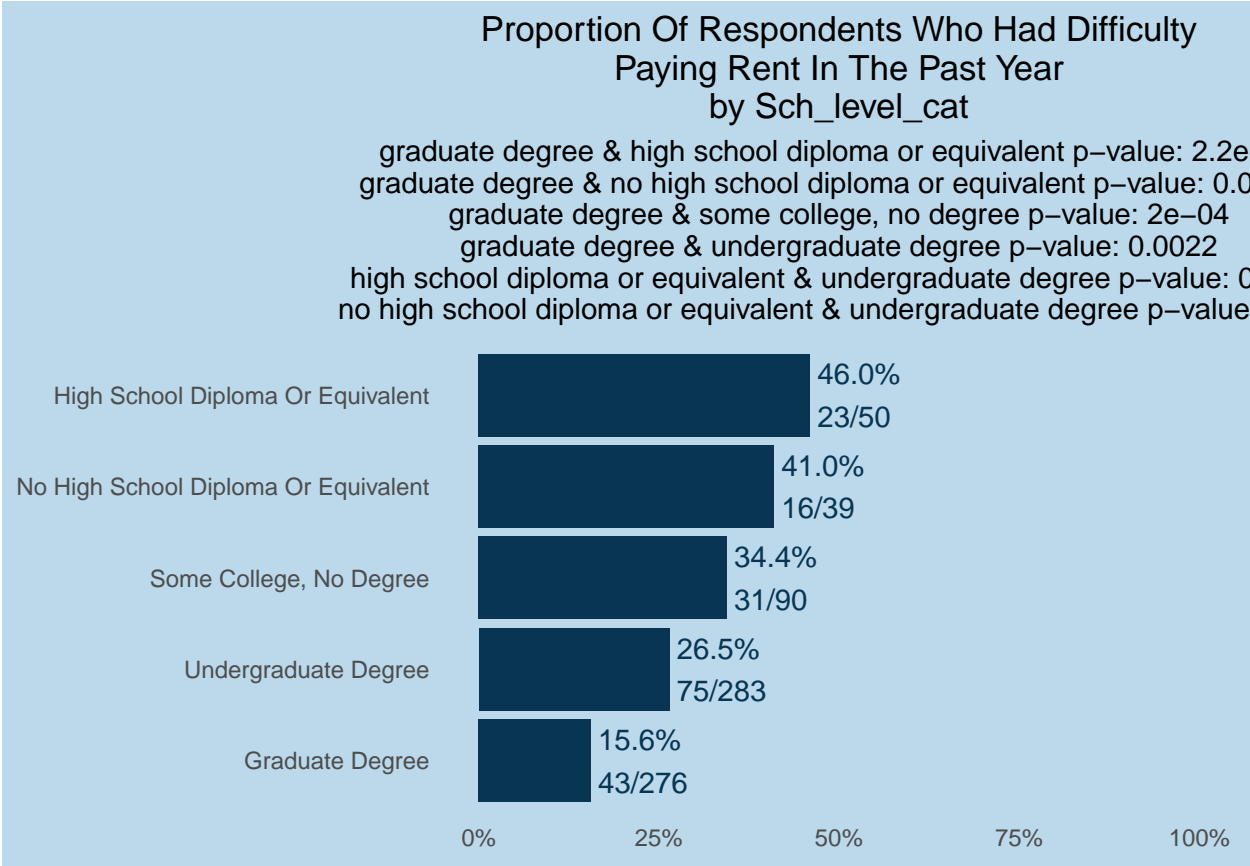
\$not_eng



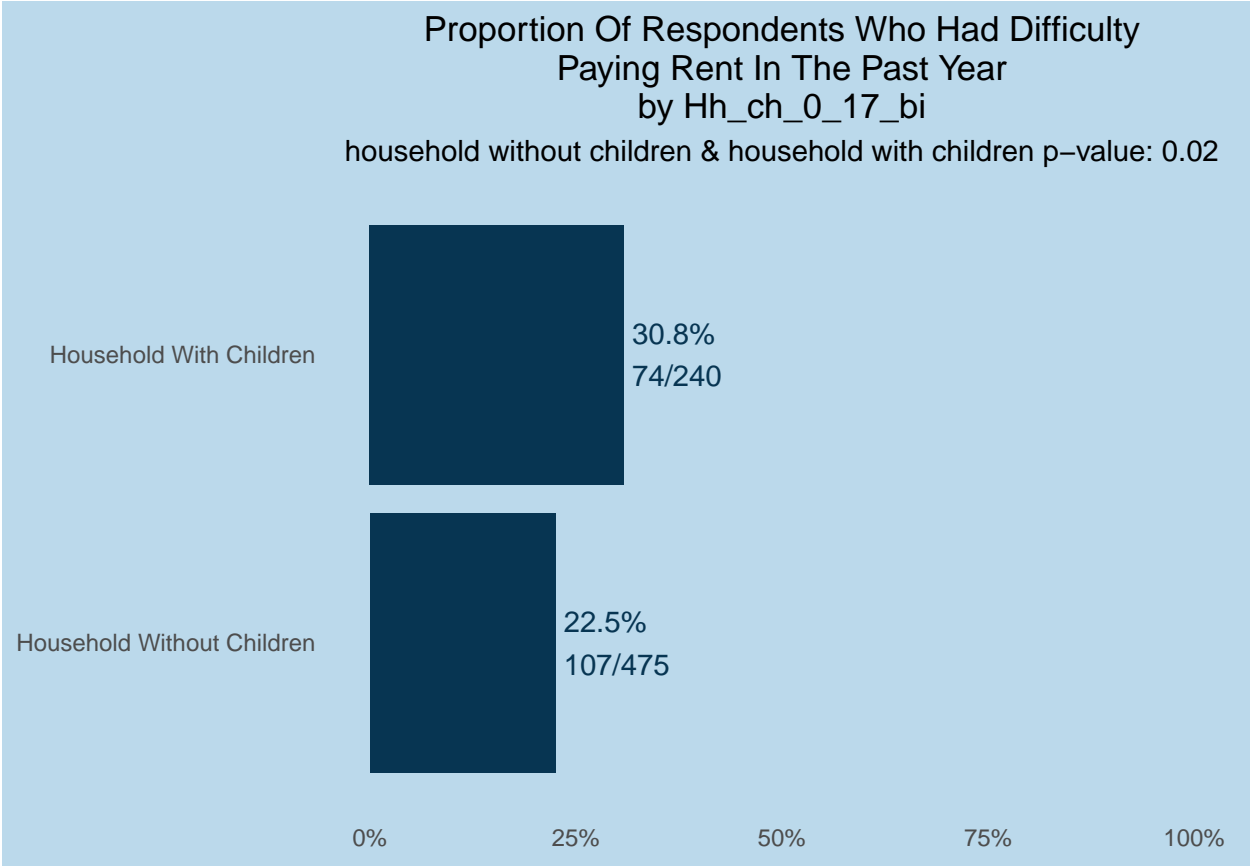
\$mar



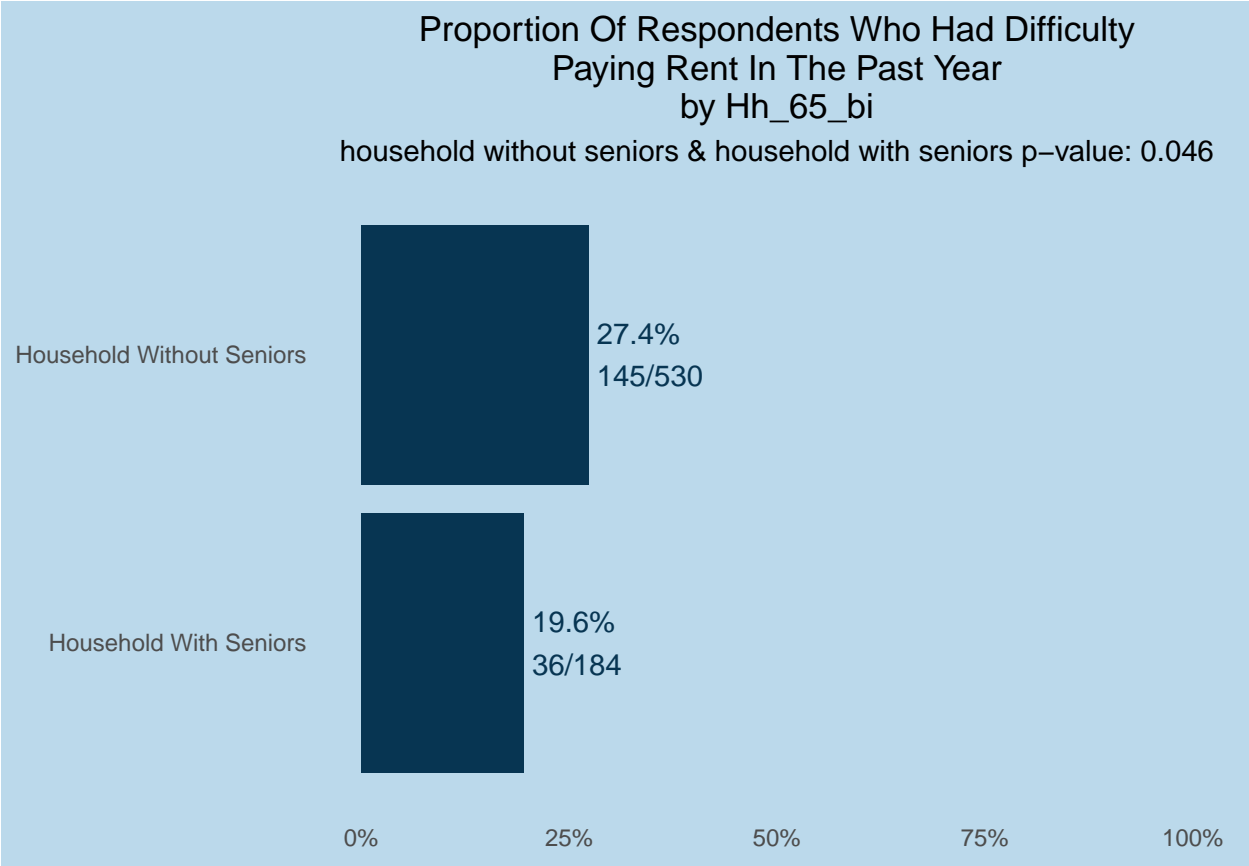
```
##  
## $sch_level_cat
```

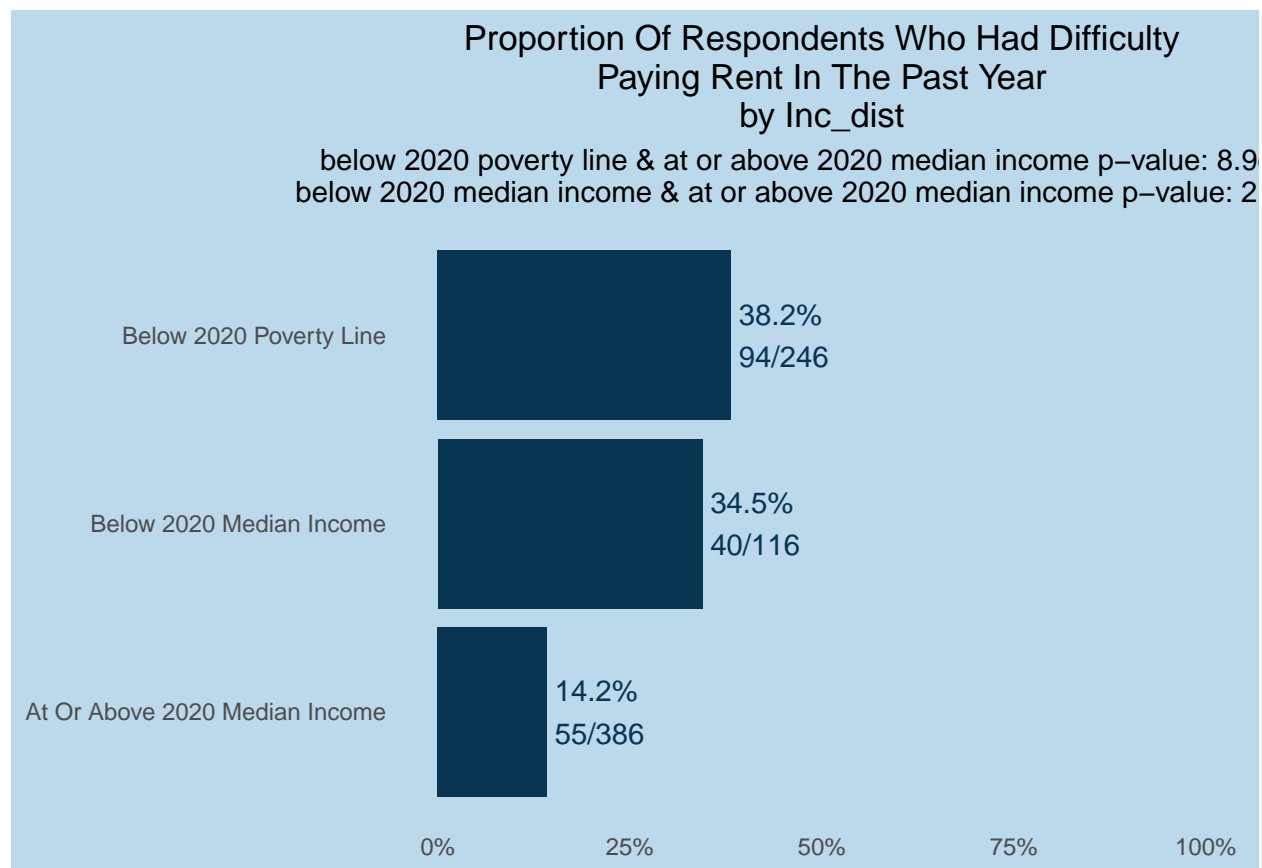
\$hh_ch_0_17_bi



\$hh_65_bi

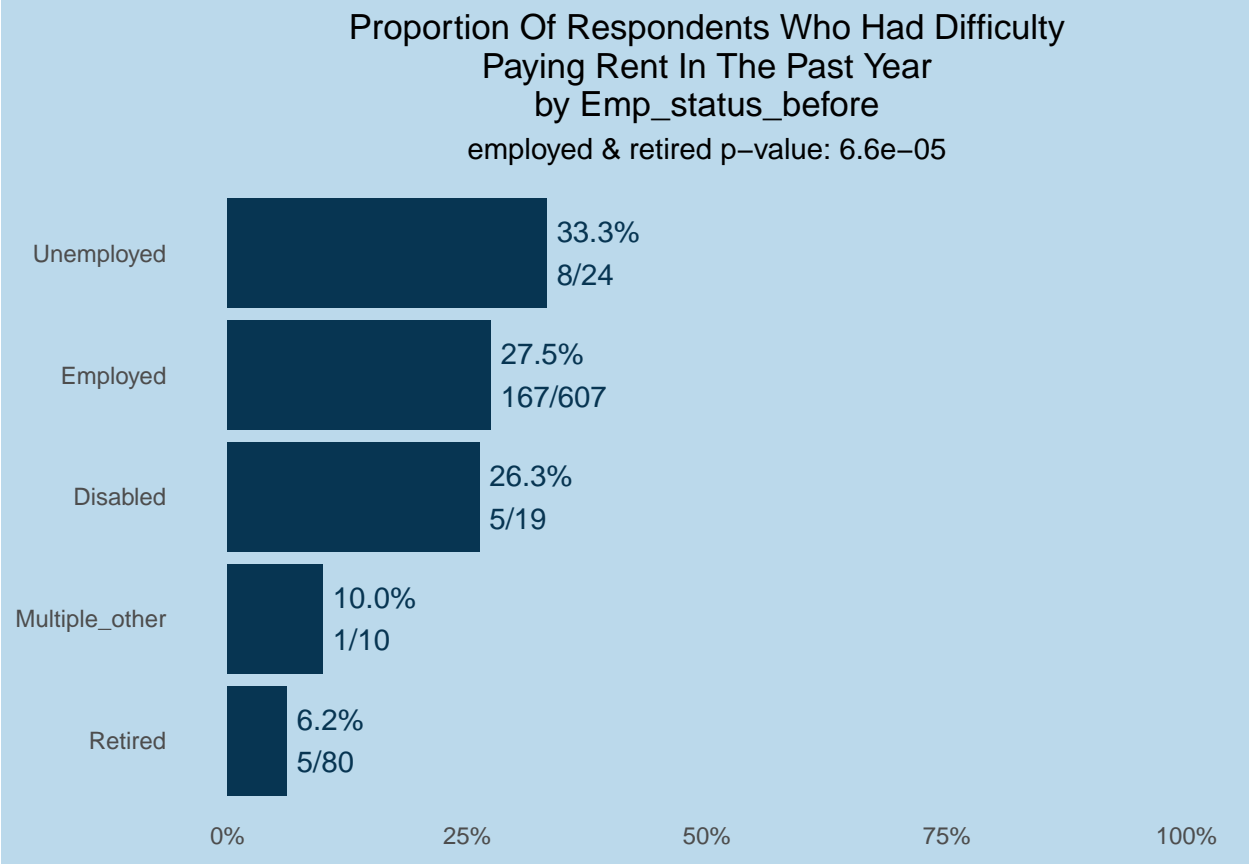


```
##  
## $inc_dist
```

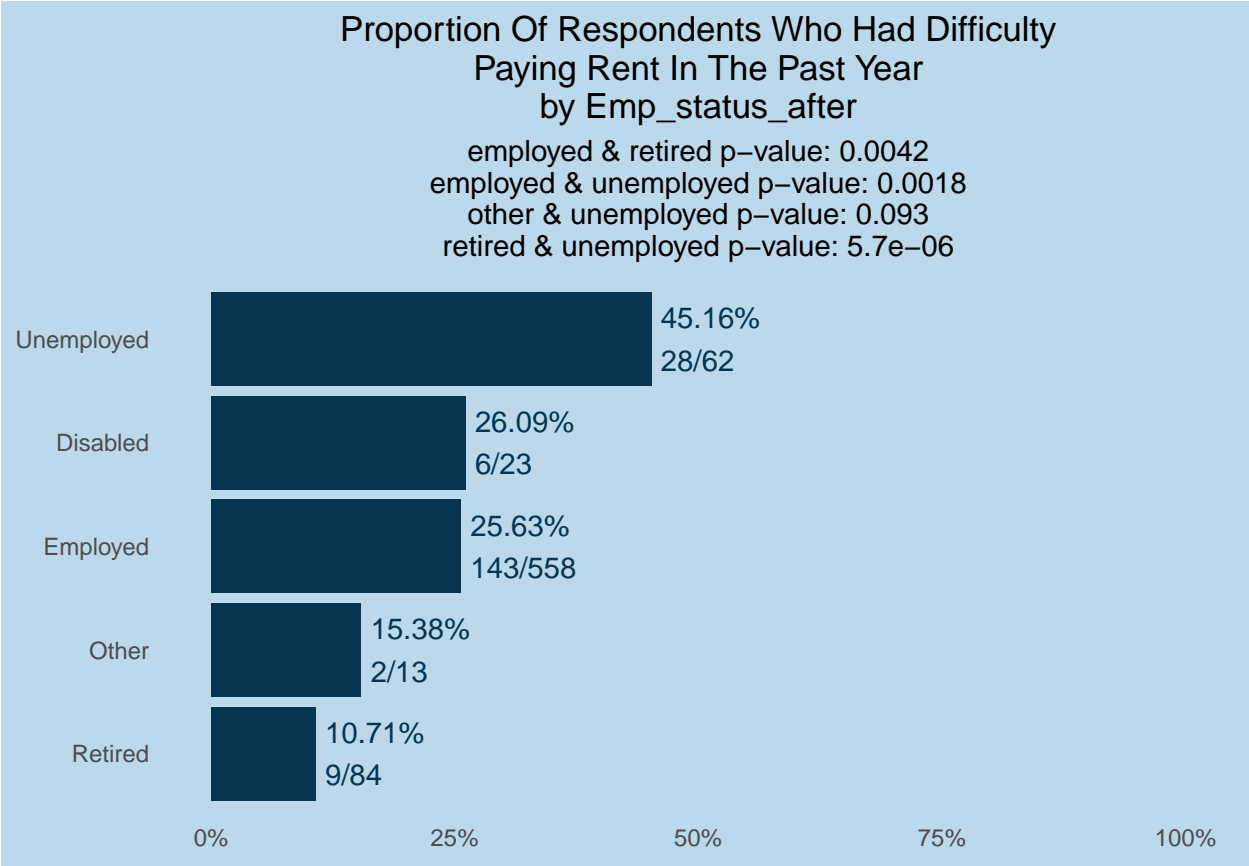


##

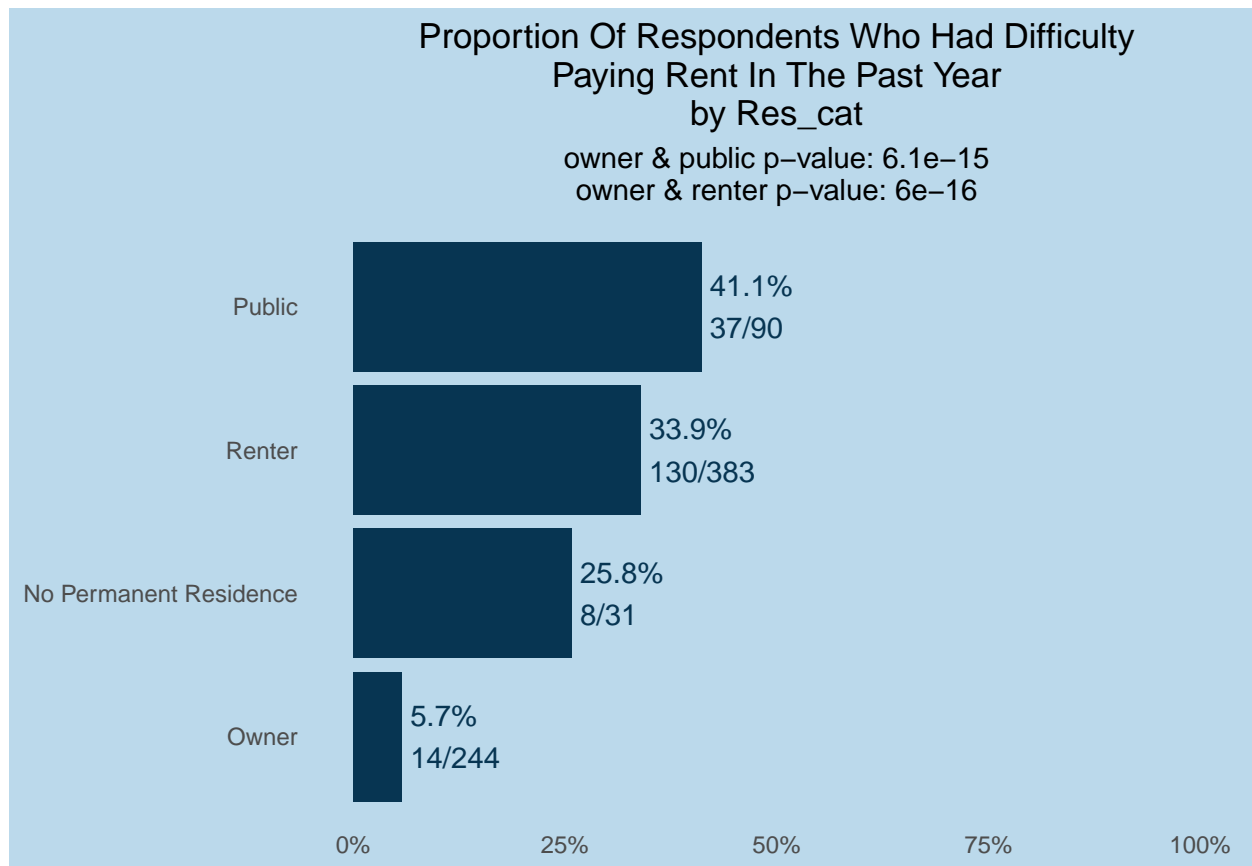
\$emp_status_before



```
##  
## $emp_status_after
```



```
##  
## $res_cat
```



2.8) Households that were financially unstable in the past year [20]

Run binary distribution over population Indicators: experienced food running out, difficulty paying bills, difficulty paying rent Yes = 1+ indicators No = 0 indicators Run binary distribution by sub-demographics (a-k) and employed/unemployed/unemployed and currently receiving unemployment benefits Compare and find gaps (test unequal proportions) Run continuous distribution over population Indicators: experienced food running out, difficulty paying bills, difficulty paying rent Very financially unstable = 3 indicators **Somewhat financially unstable = 1-2 indicators** Not financially unstable = 0 indicators

Findings (some statistically significant findings)

- respondents who owned their residences had statistically significantly less financial insecurity
- again, respondents who spoke a language other than english at home experienced more financial insecurity
- again, elderly respondents and households with seniors had less financial insecurity
- on the other hand, households with children had more financial insecurity
- Black and Hispanic respondents had more financial insecurity than white respondents
- school level was positively associated with financial security (more school, more security)
- and obviously, unemployed respondents were more financially unstable than employed respondents

```
mean(wrangled$fin_unstable, na.rm = TRUE)
```

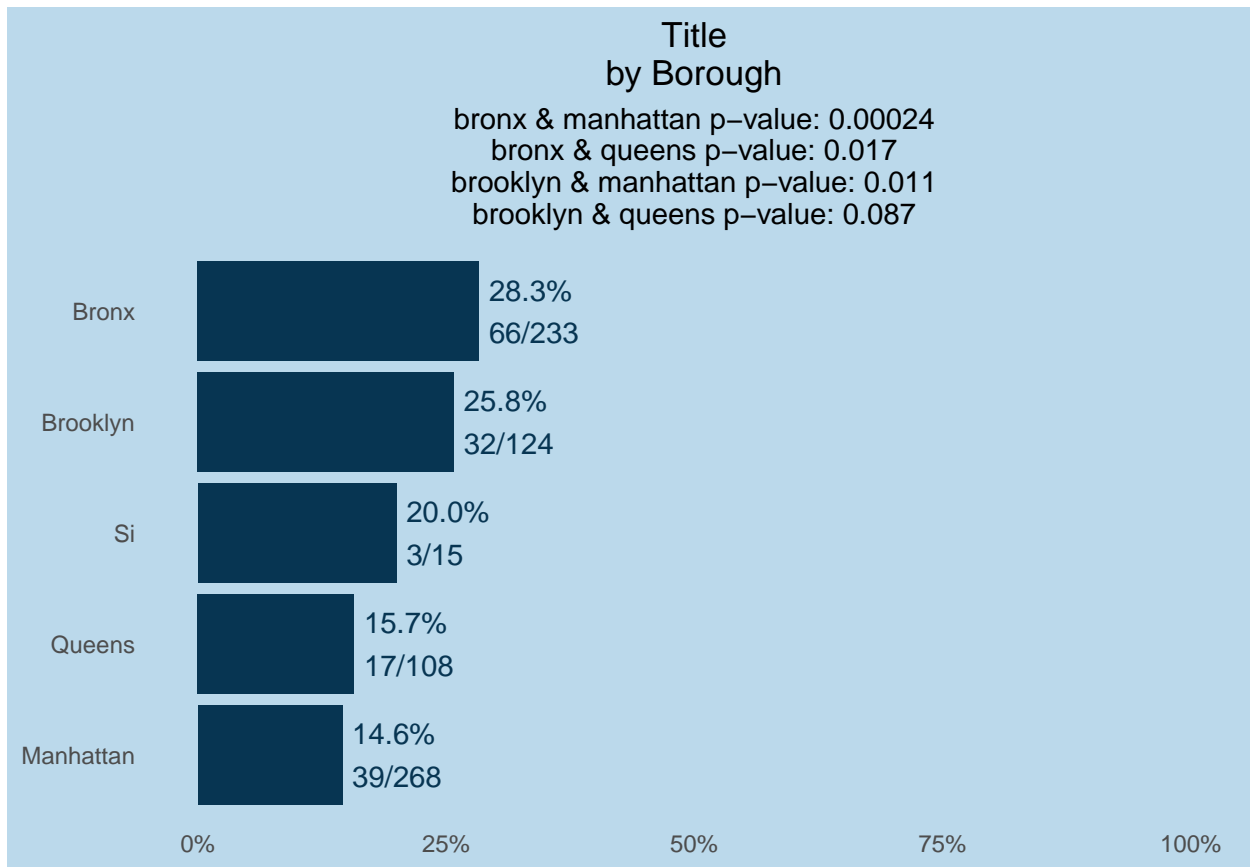
```
## [1] 0.209893
```

```
wrangled %>% filter(is.na(diff_ran_out), !is.na(diff_bill))
```

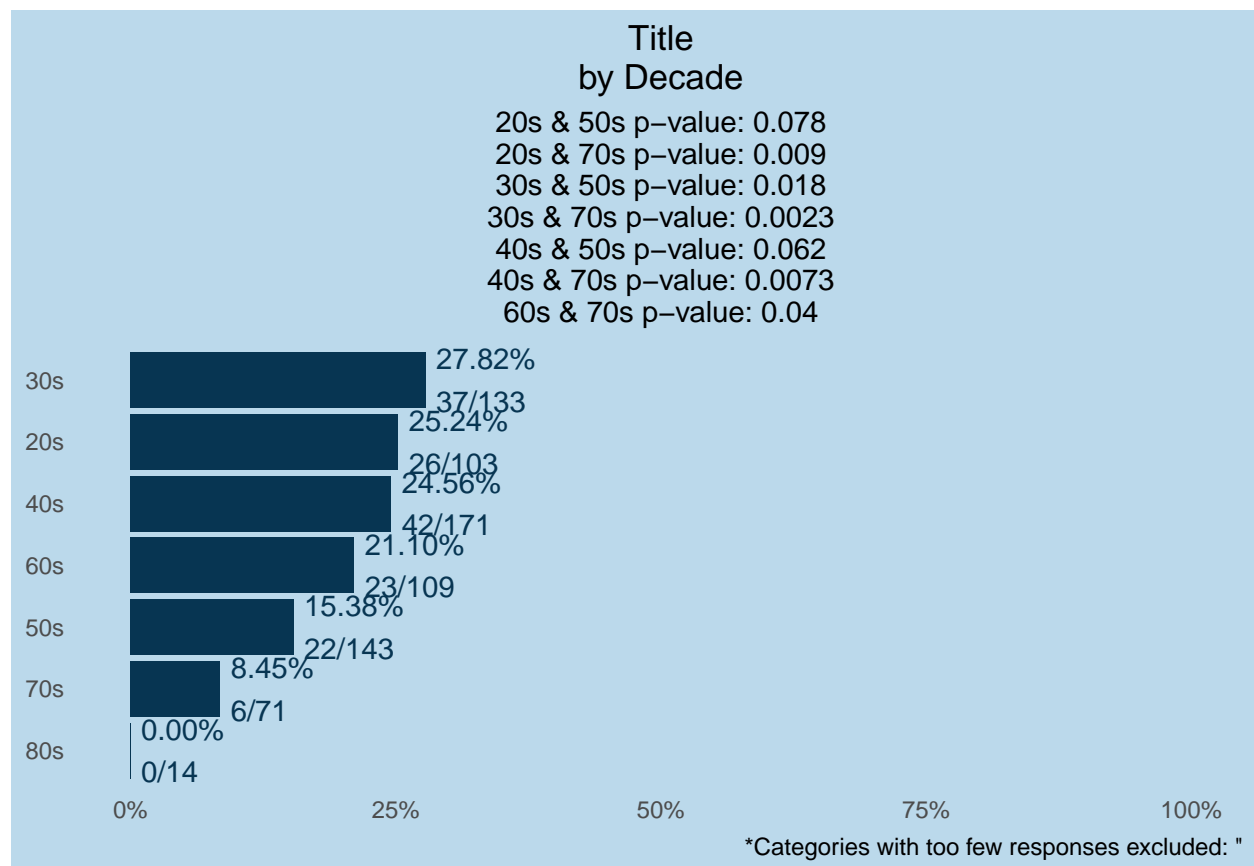
```
## # A tibble: 0 x 268
## # ... with 268 variables: responseid <chr>, recordeddate <dtm>, source <chr>,
## #   duration <int>, progress <int>, resi_ny <int+lbl>, zip <chr>,
## #   intersection <chr>, age <dbl>, gen <int+lbl>, gen_text <chr>, race <chr>,
## #   race_his_lat <int+lbl>, race_white <int+lbl>, race_black <int+lbl>,
## #   race_indian <int+lbl>, race_asian <int+lbl>, race_other <int+lbl>,
## #   race_pnta <int+lbl>, race_haw <int+lbl>, race_text <chr>, mar <int+lbl>,
## #   relig <int+lbl>, relig_text <chr>, sex_orient <int+lbl>, ...
```

```
make_plots(wrangled, demographics, hyp_var = "fin_unstable", min = 10)
```

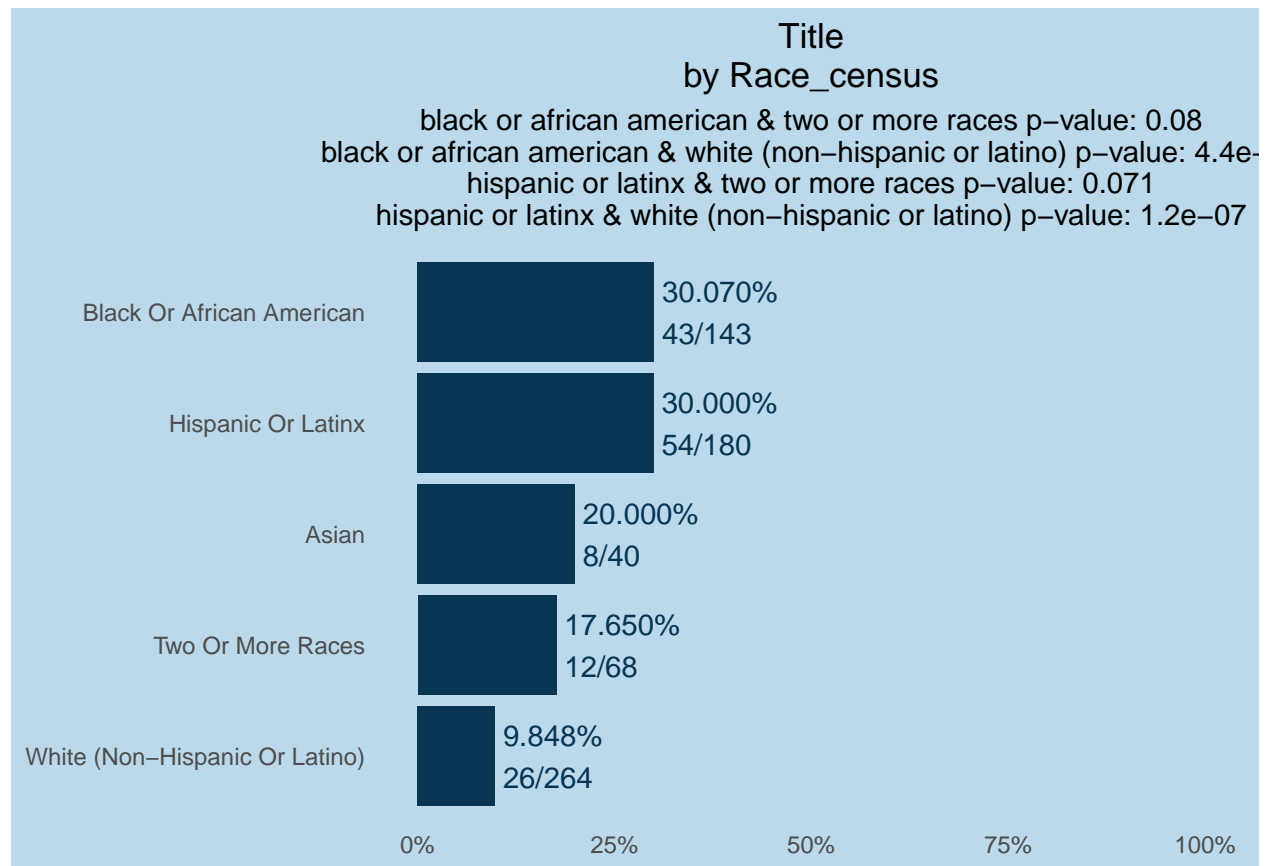
```
## $borough
```



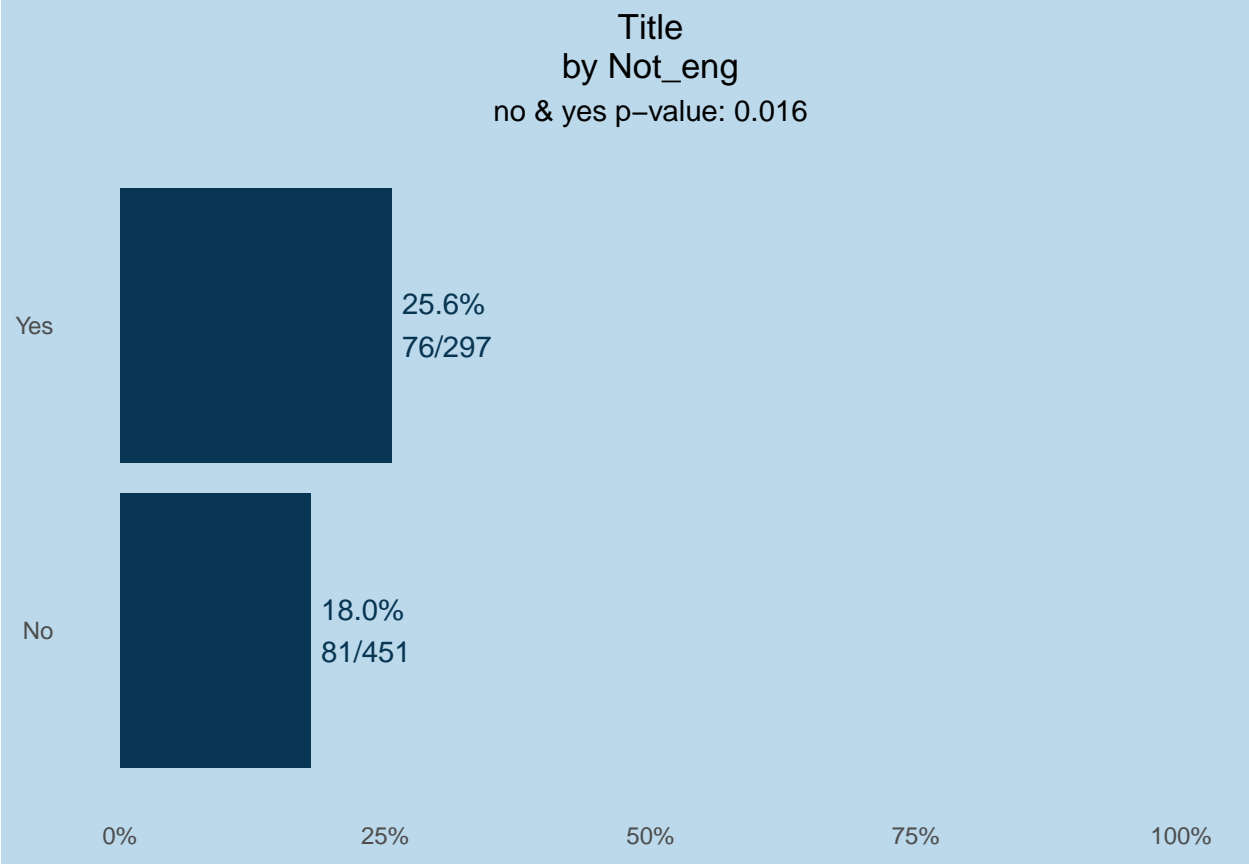
```
##
## $decade
```

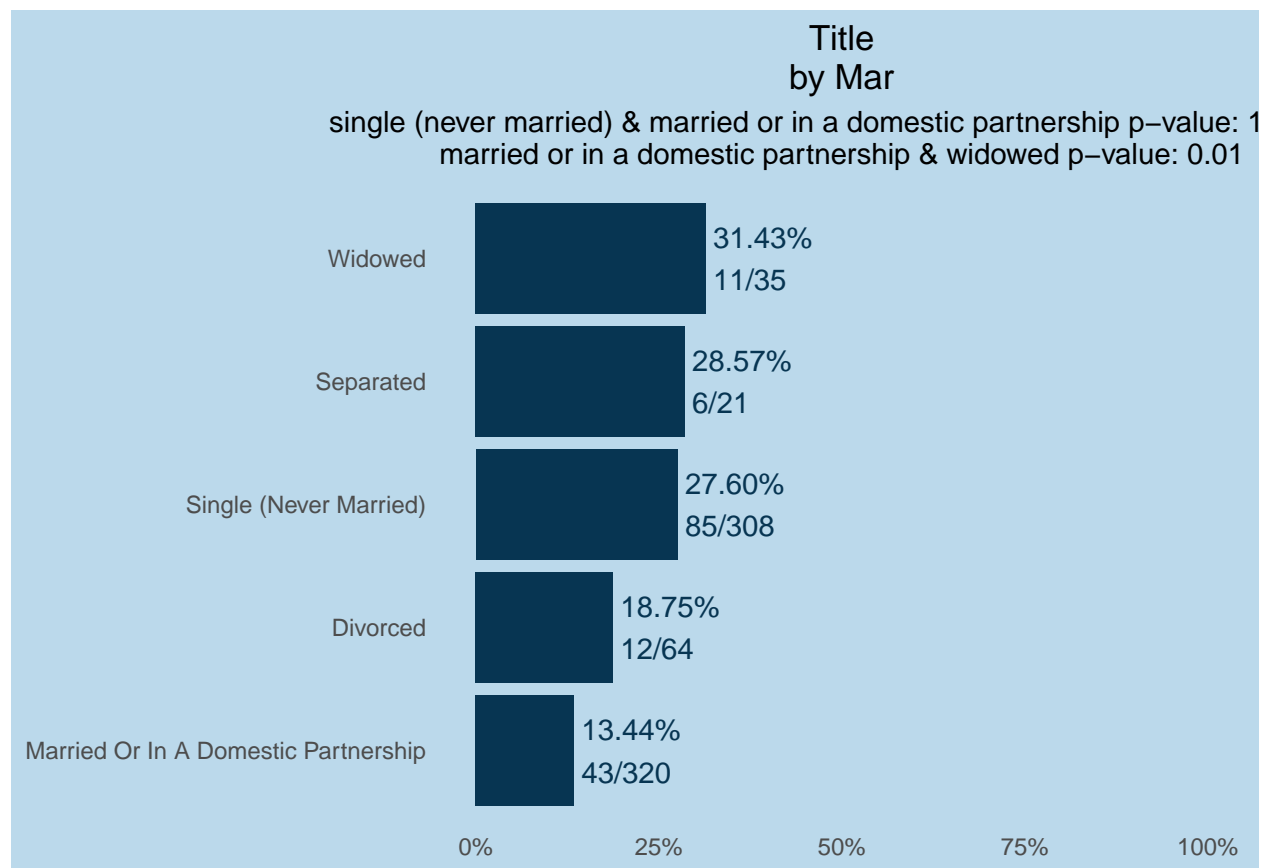
```
##
## $gen
## NULL
##
## $race_census
```



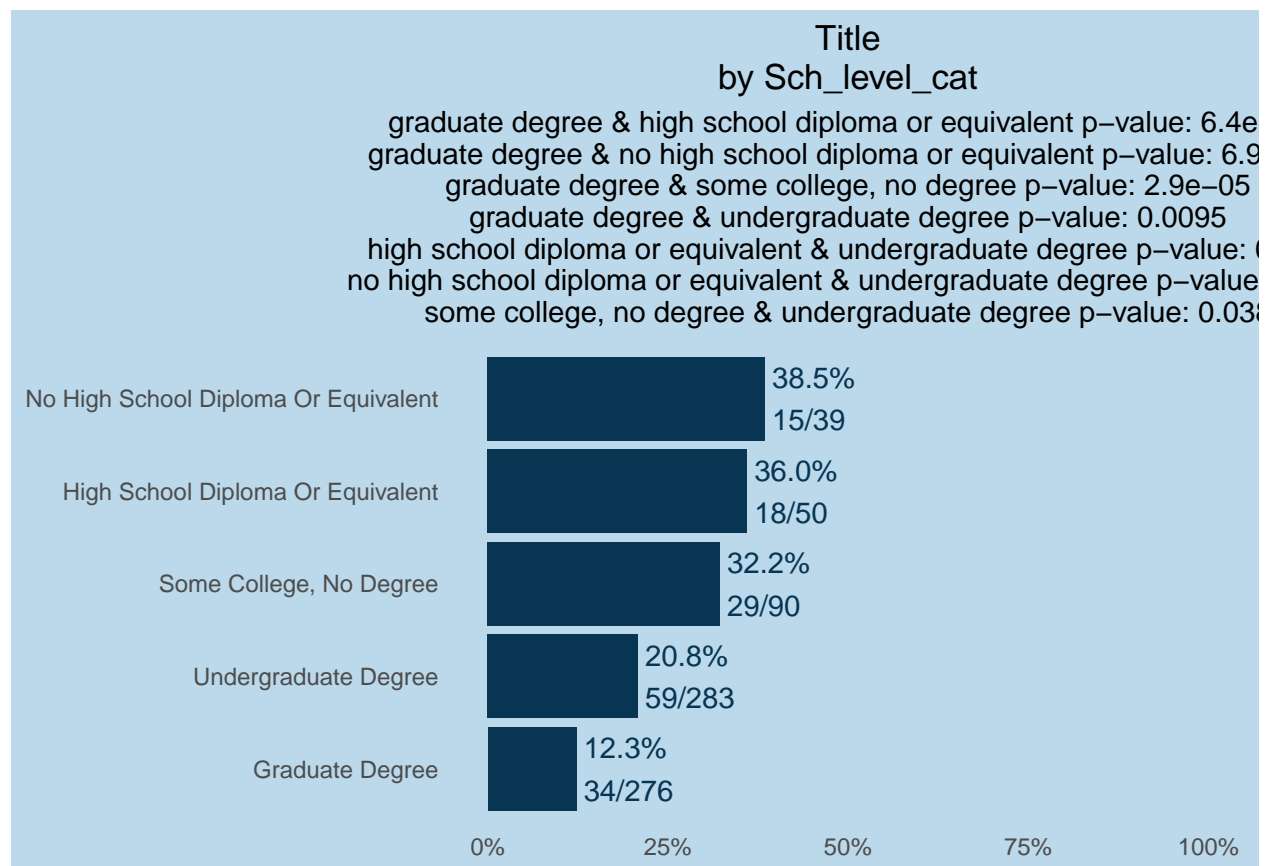
\$not_eng



\$mar

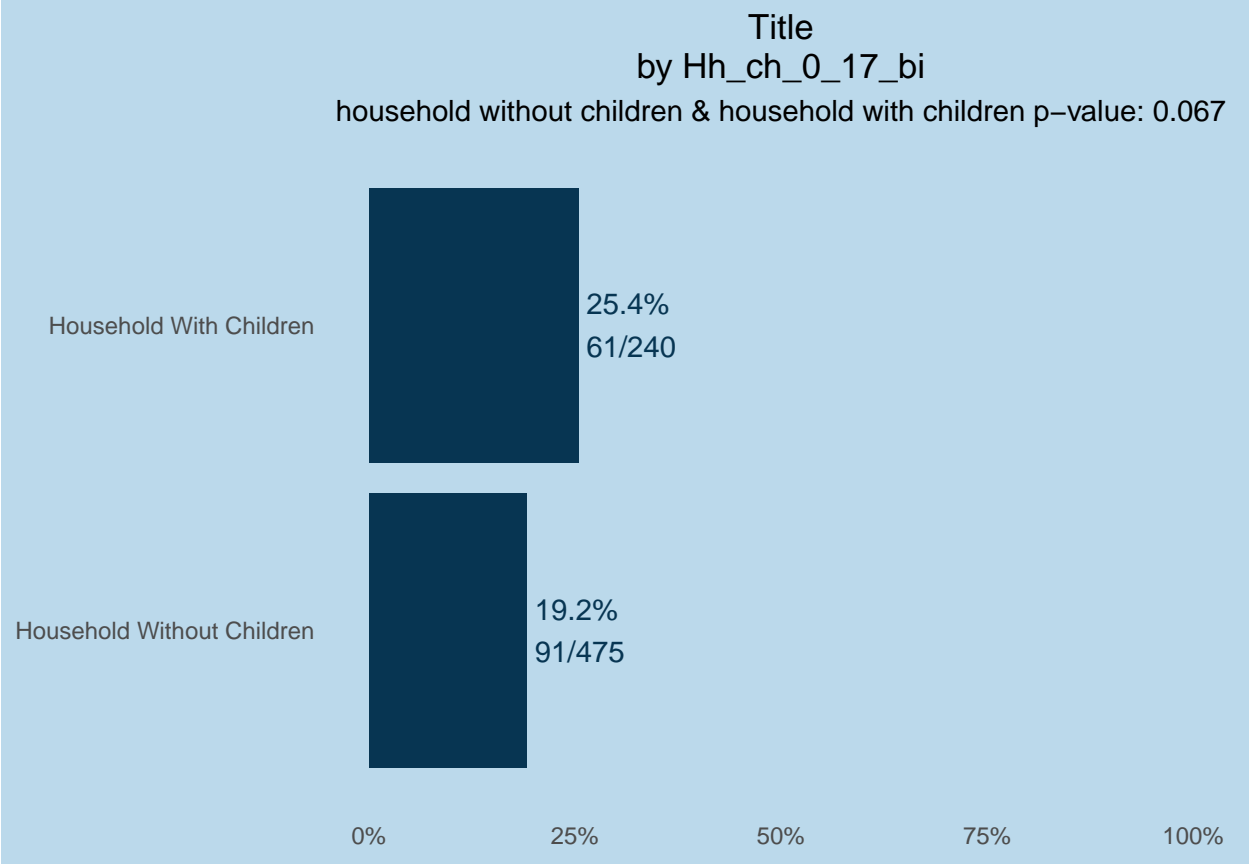


```
##
## $sch_level_cat
```

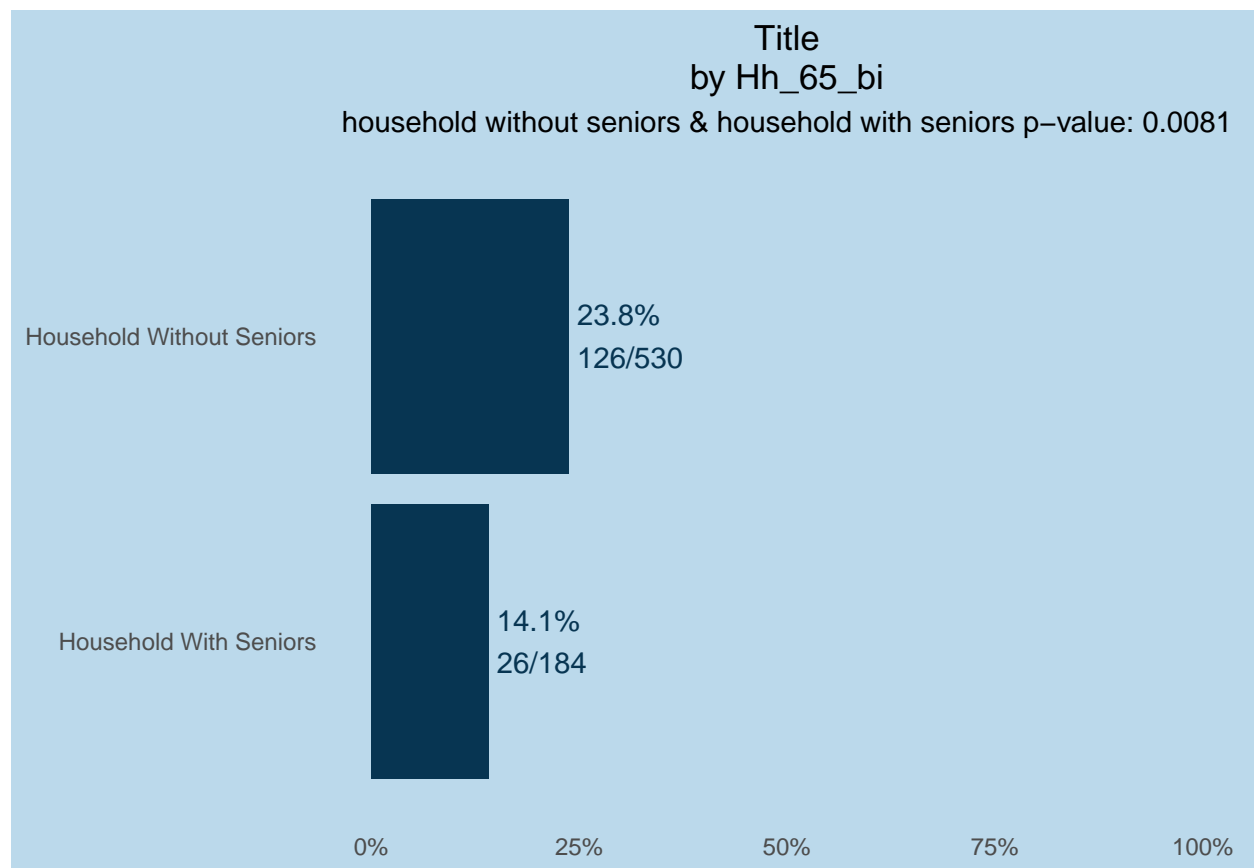


##

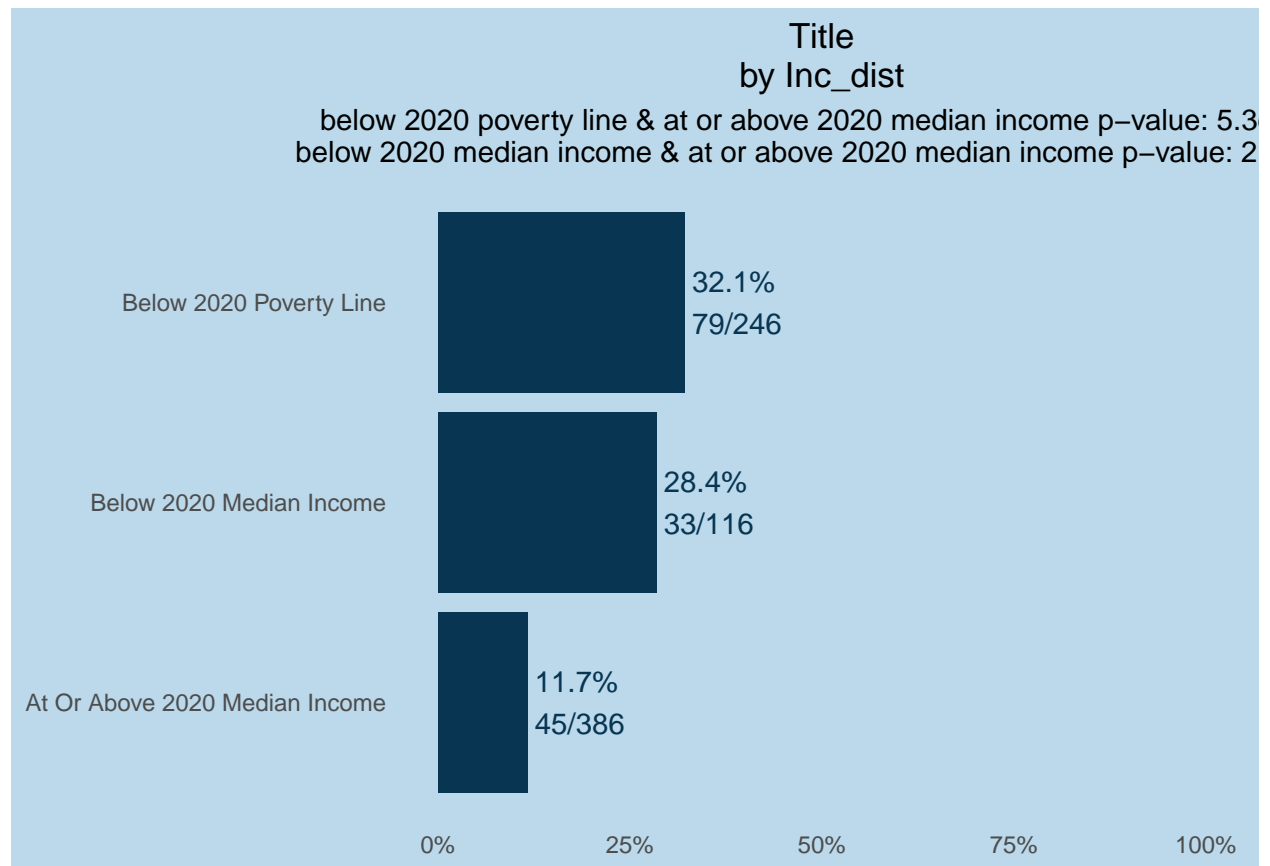
\$hh_ch_0_17_bi



\$hh_65_bi

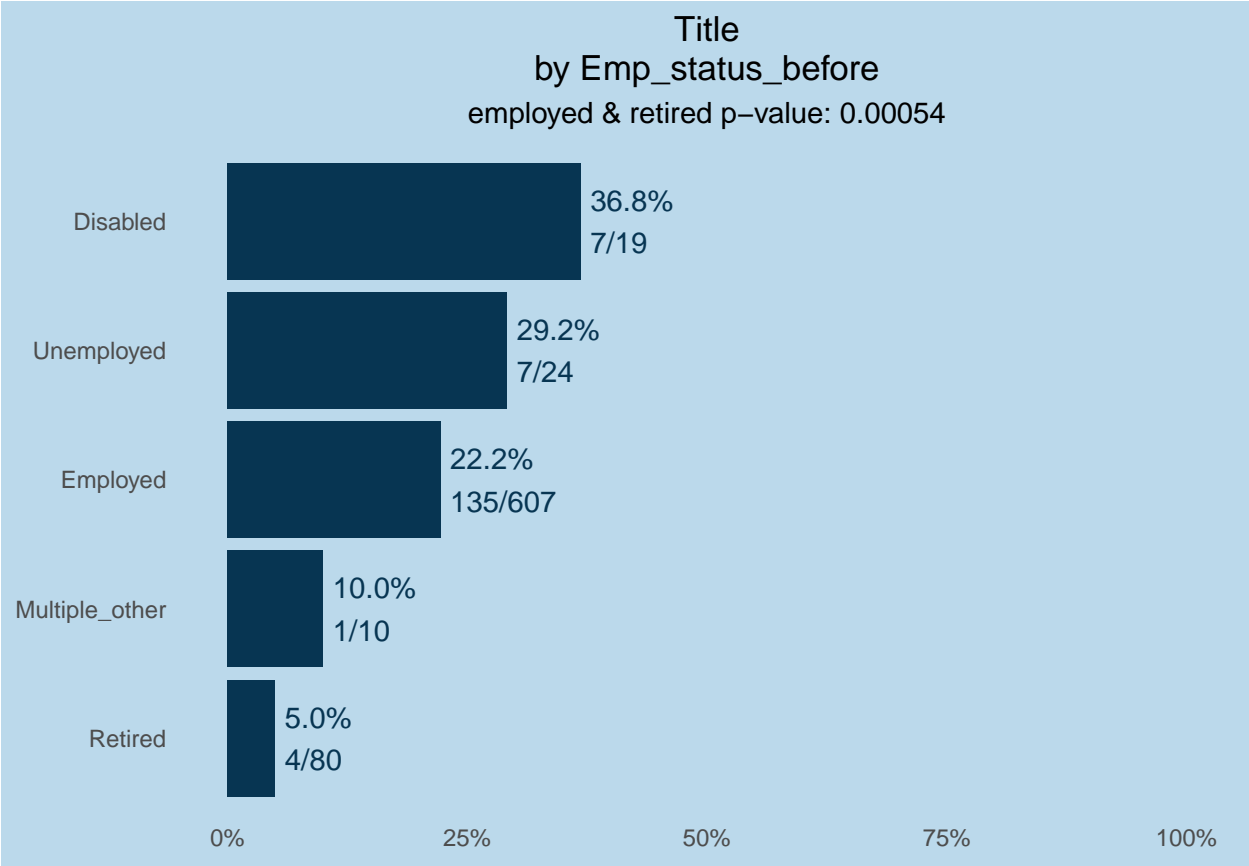


\$inc_dist

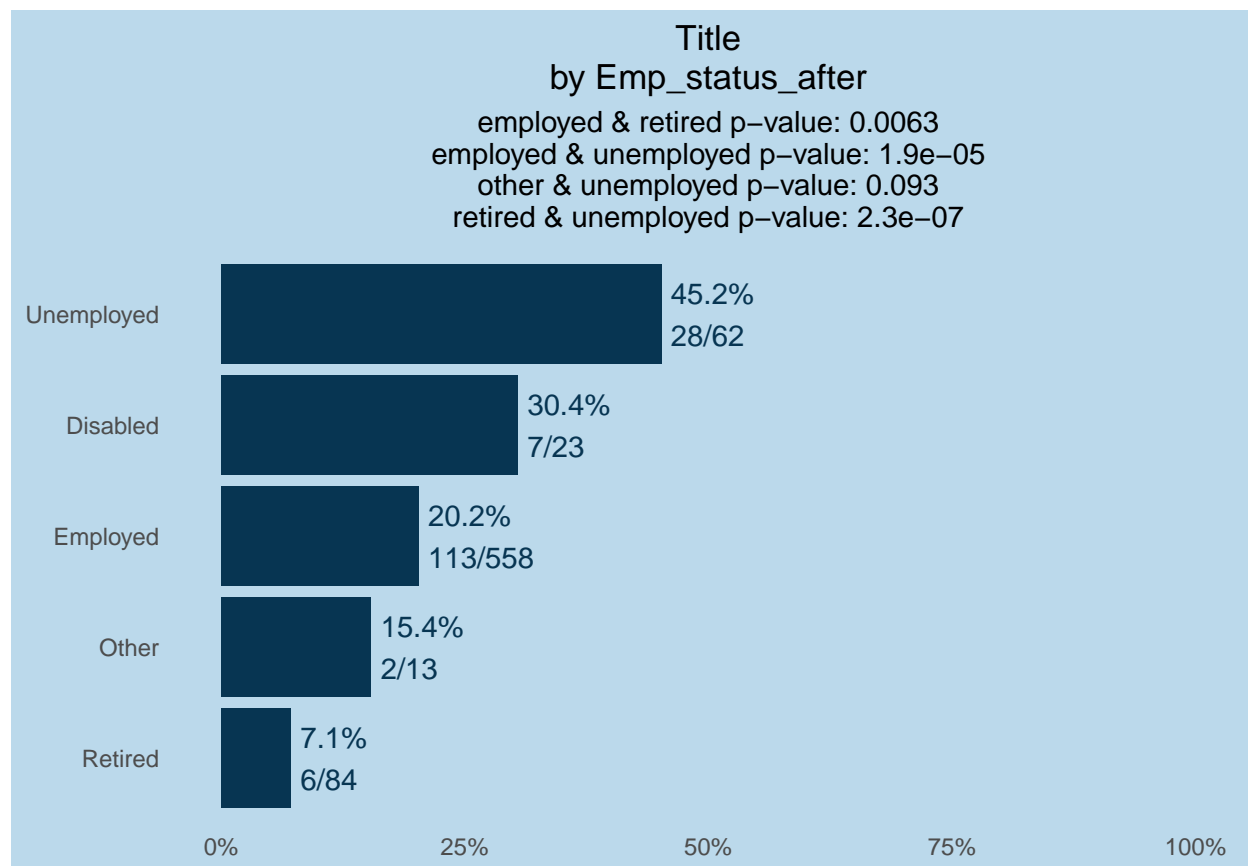


##

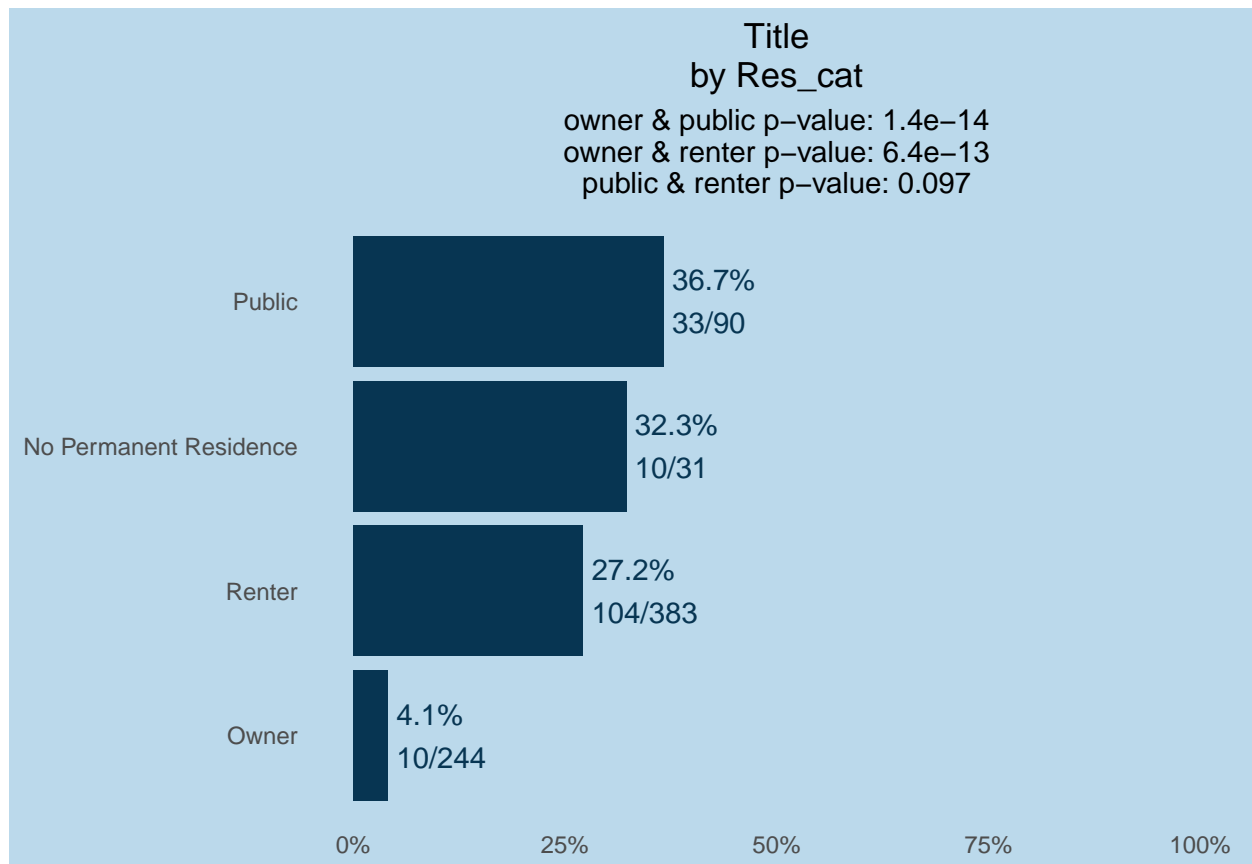
\$emp_status_before



```
##  
## $emp_status_after
```



```
##  
## $res_cat
```



2.9) Households that experienced food insecurity in the past year [20]

Run binary distribution over population Indicators: worried about food running out, ran out of food/ unable to afford food Yes = 1+ indicator No = 0 indicators Run continuous distribution over population Indicators: worried about food running out, ran out of food/ unable to afford food Very food insecure = 2 indicators Somewhat food insecure = worried about food not lasting (OR experienced food bought didn't last i.e. 1 indicator?) Not food insecure = 0 indicators

Findings (some statistically significant findings)

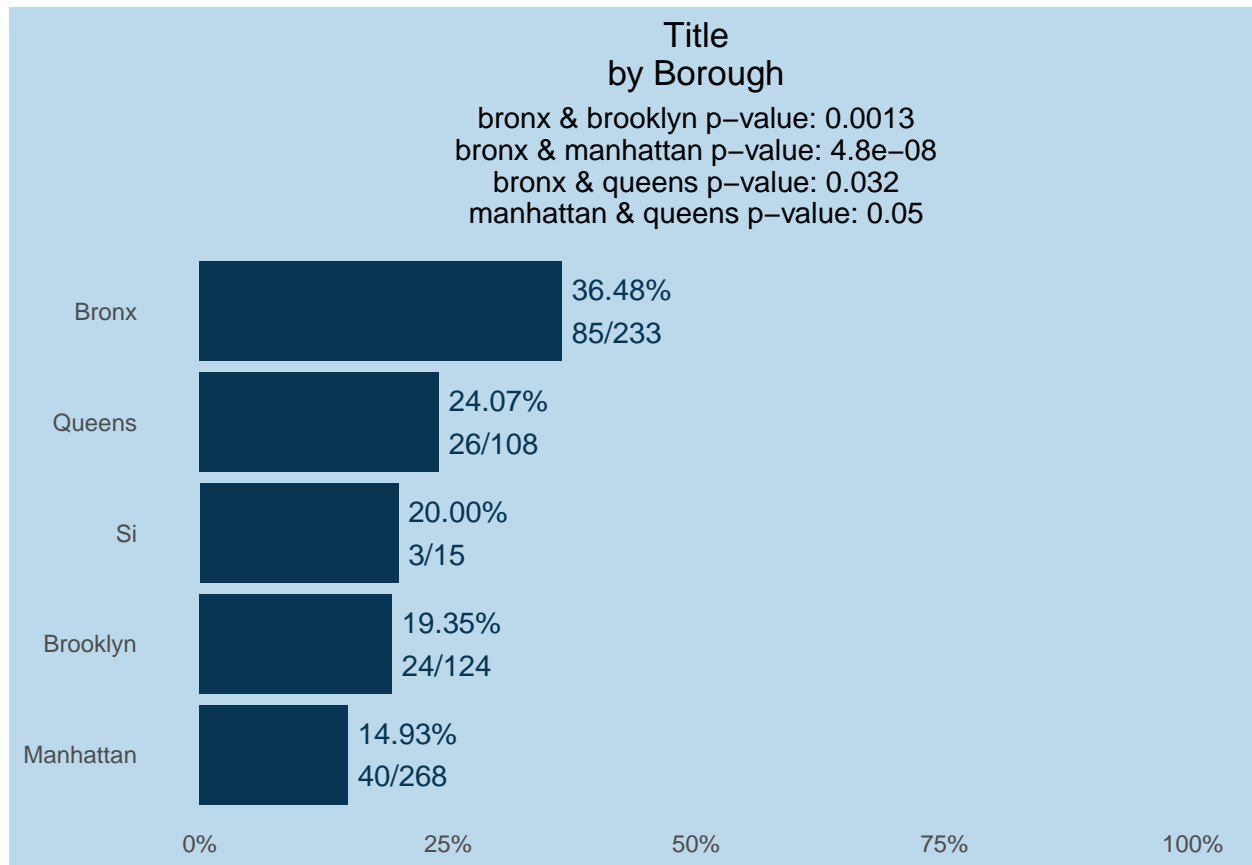
- respondents who owned their residences had statistically significantly less food insecurity (10%) compared to respondents without a permanent residence (50%)
- again, respondents who spoke a language other than english at home experienced more food insecurity
- again, elderly respondents, households with seniors, and retired respondents all experienced less food insecurity
- on the other hand, households with children had more food insecurity (responds to hyp 2.10)
- Black and Hispanic respondents had significantly more food insecurity than white respondents
- school level and income bracket was negatively associated with food insecurity (more school, more security)
- and obviously, unemployed respondents were more financially unstable than employed respondents

```
mean(wrangled$food_insec, na.rm = TRUE)
```

```
## [1] 0.2379679
```

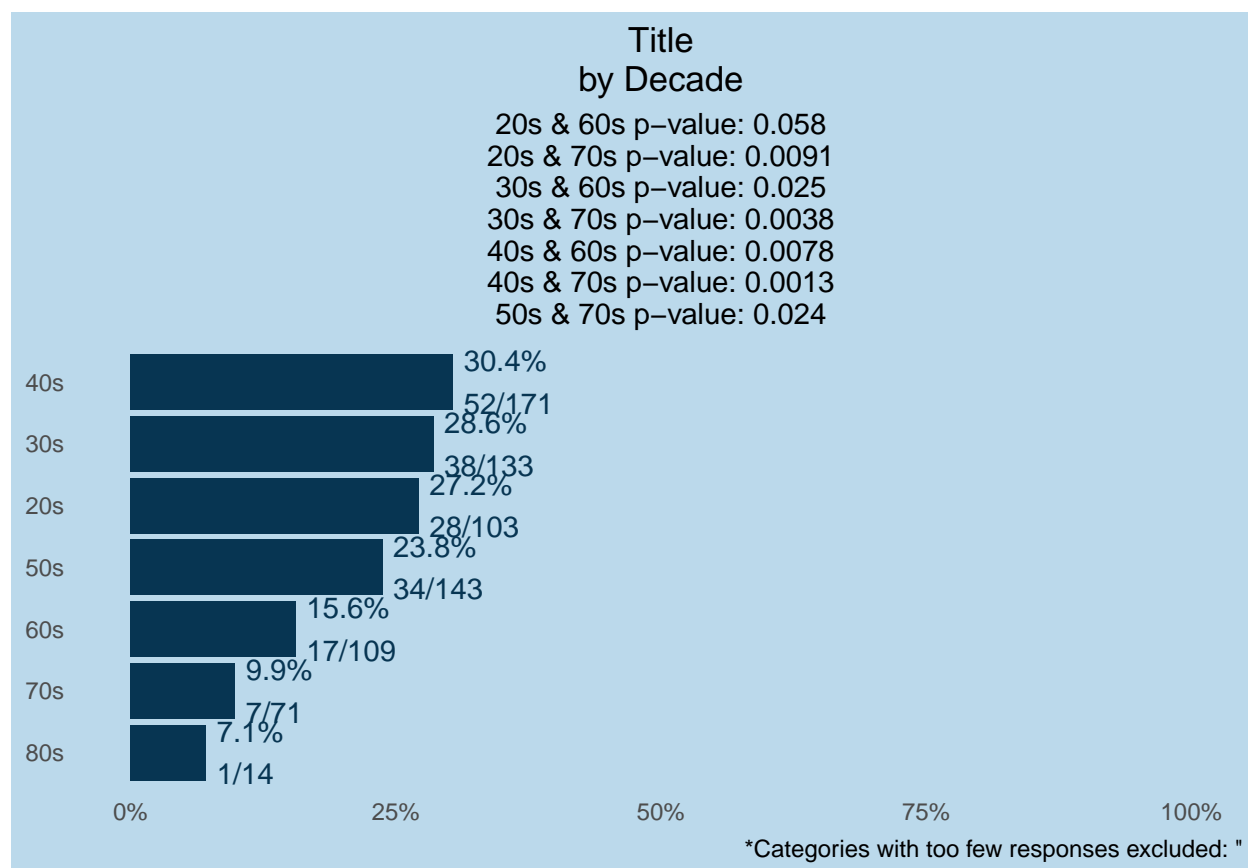
```
make_plots(wrangled, demographics, "food_insec", min = 7)[-6]
```

```
## $borough
```

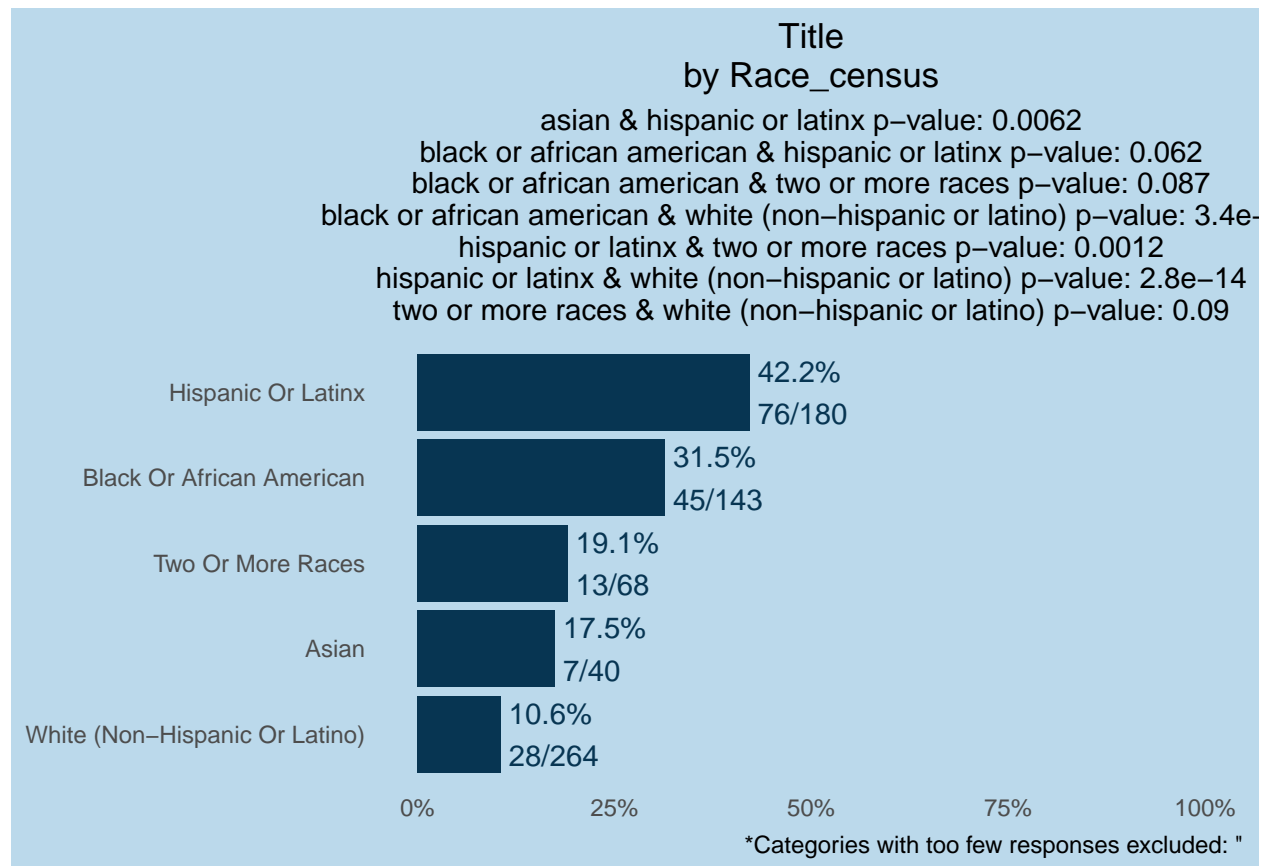


```
##
```

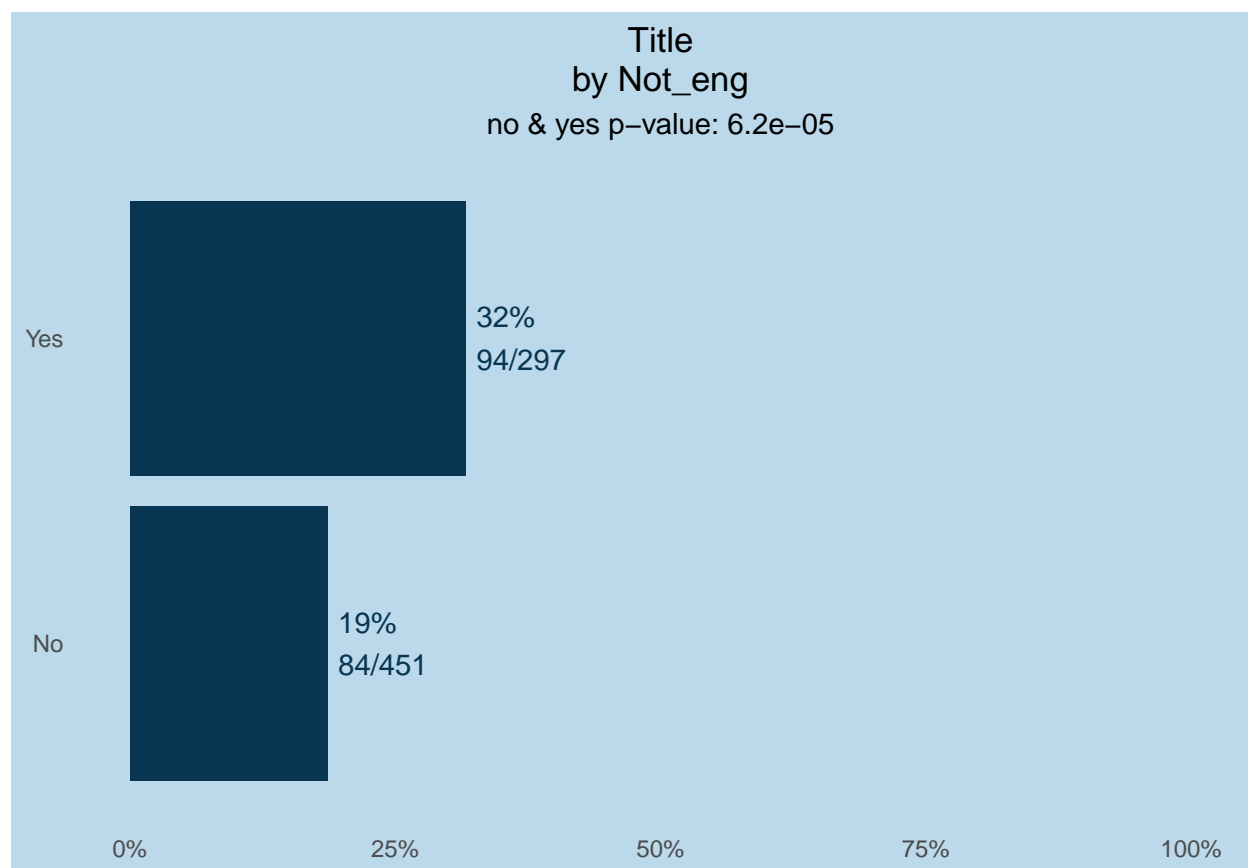
```
## $decade
```



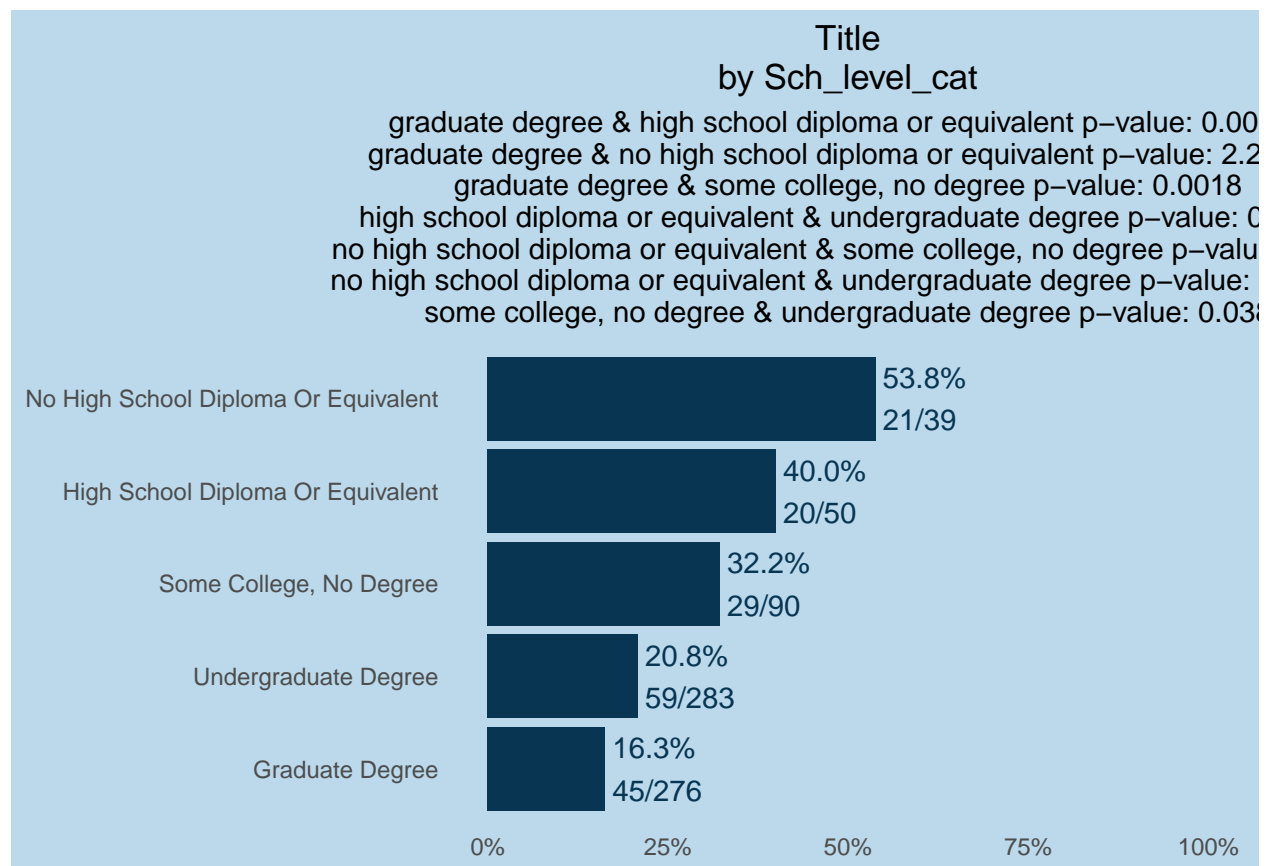
```
##
## $gen
## NULL
##
## $race_census
```



\$not_eng

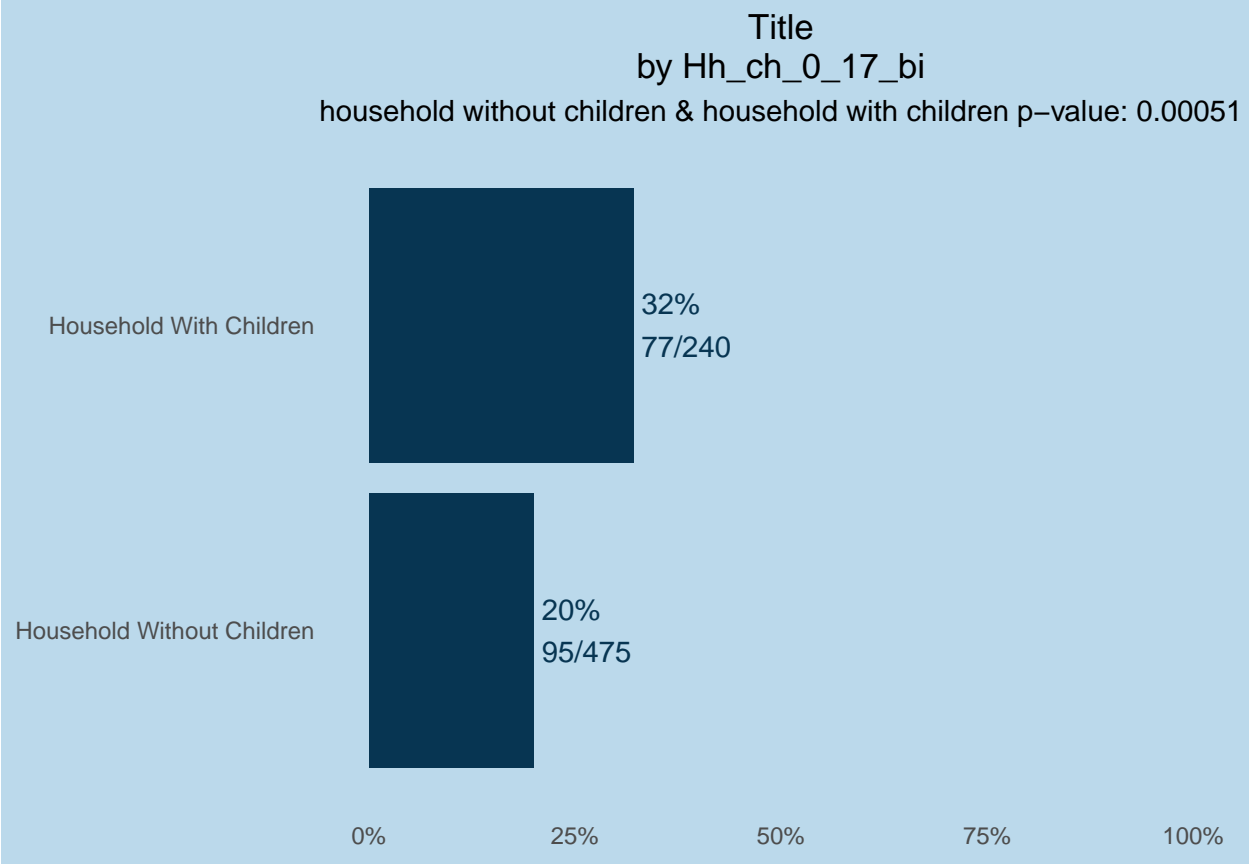


```
##  
## $sch_level_cat
```

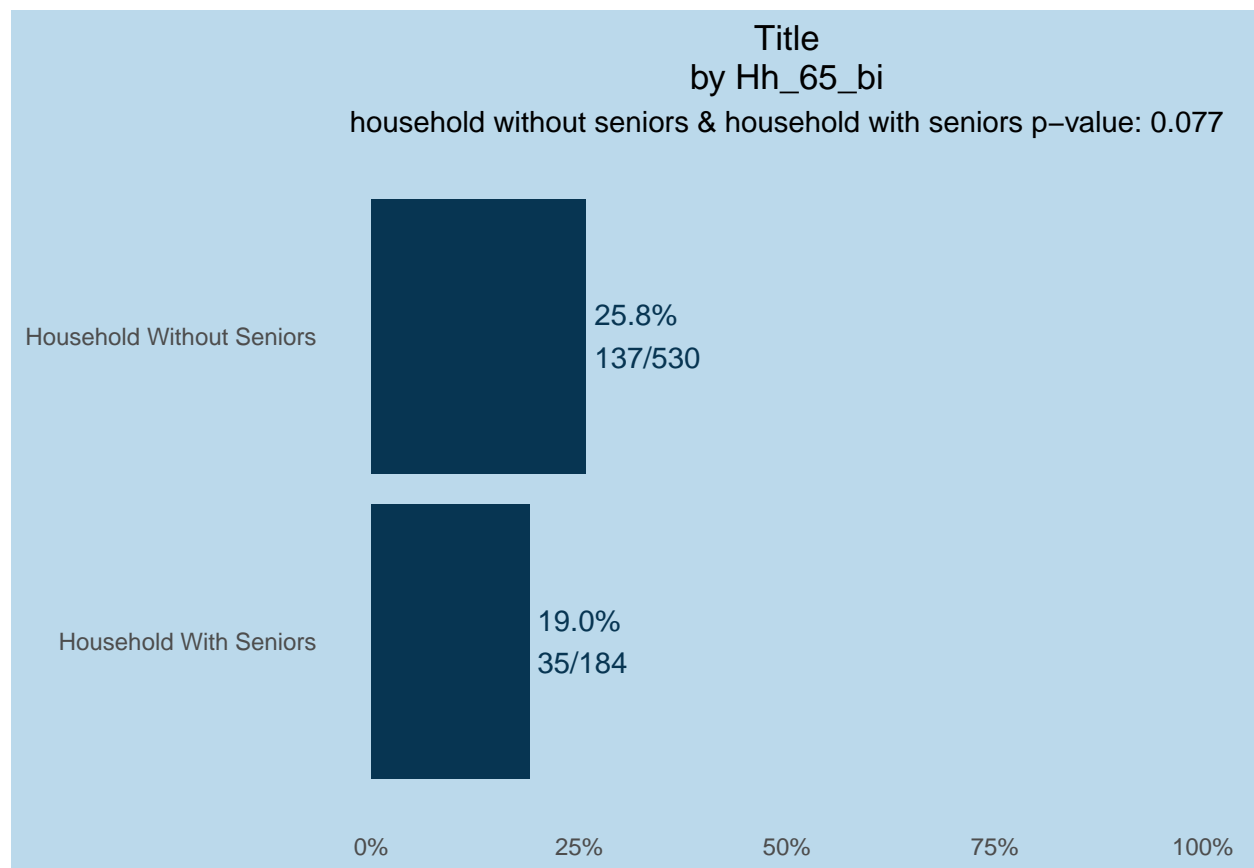


##

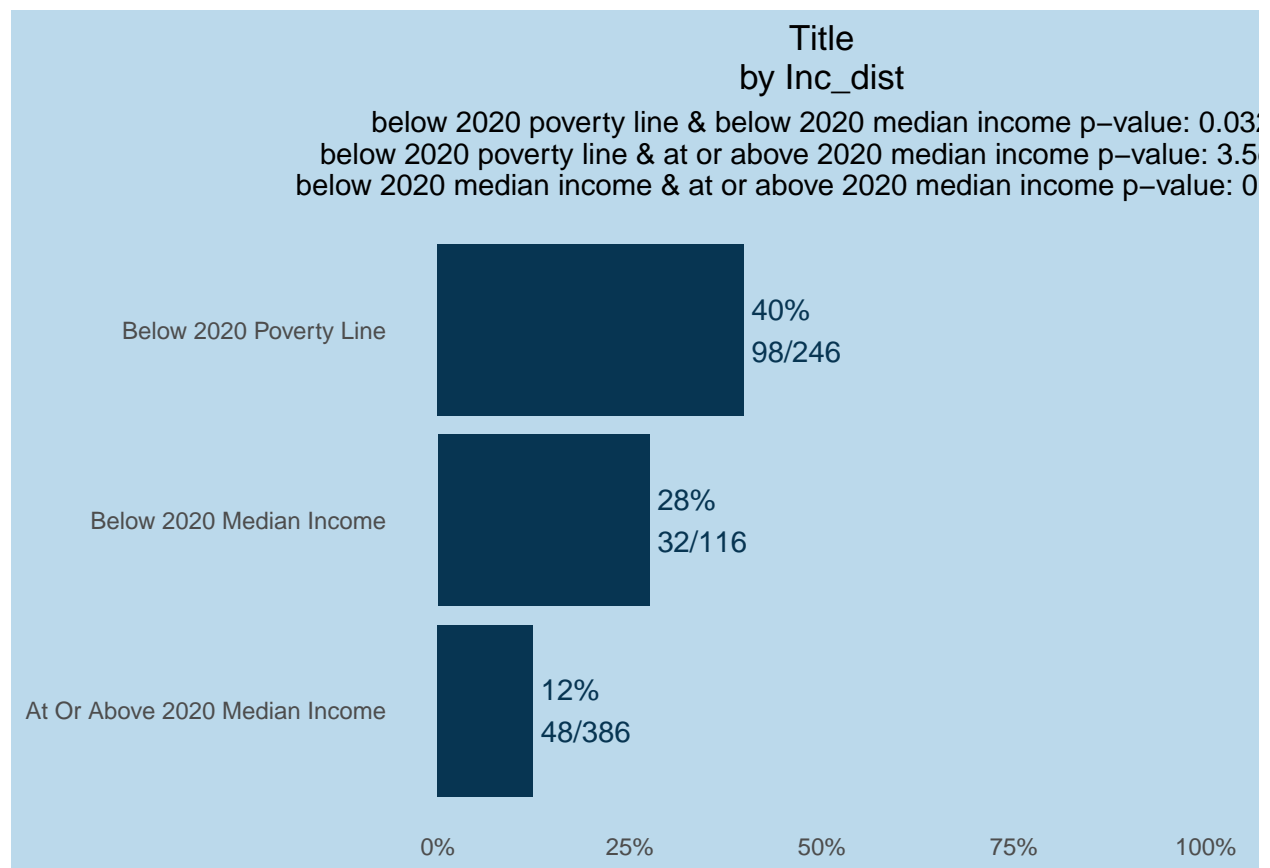
\$hh_ch_0_17_bi



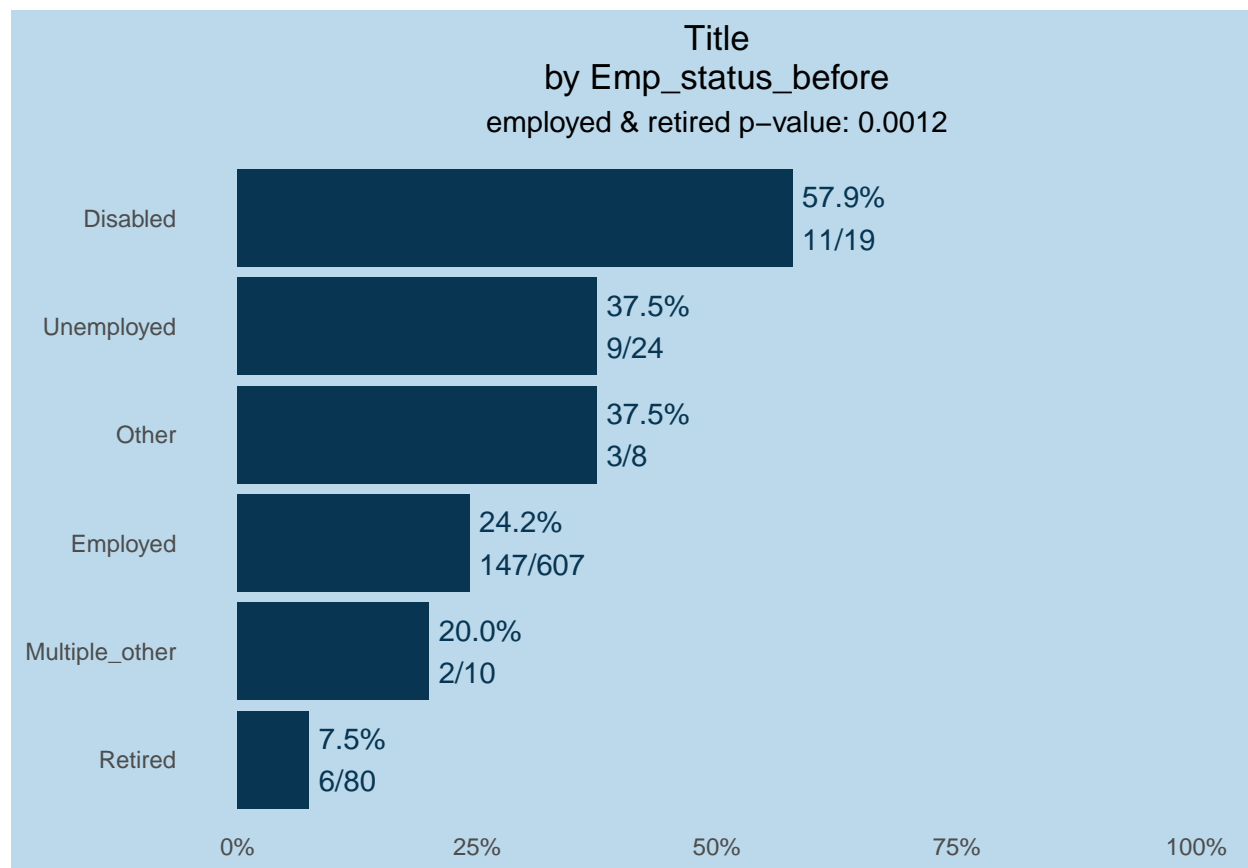
\$hh_65_bi



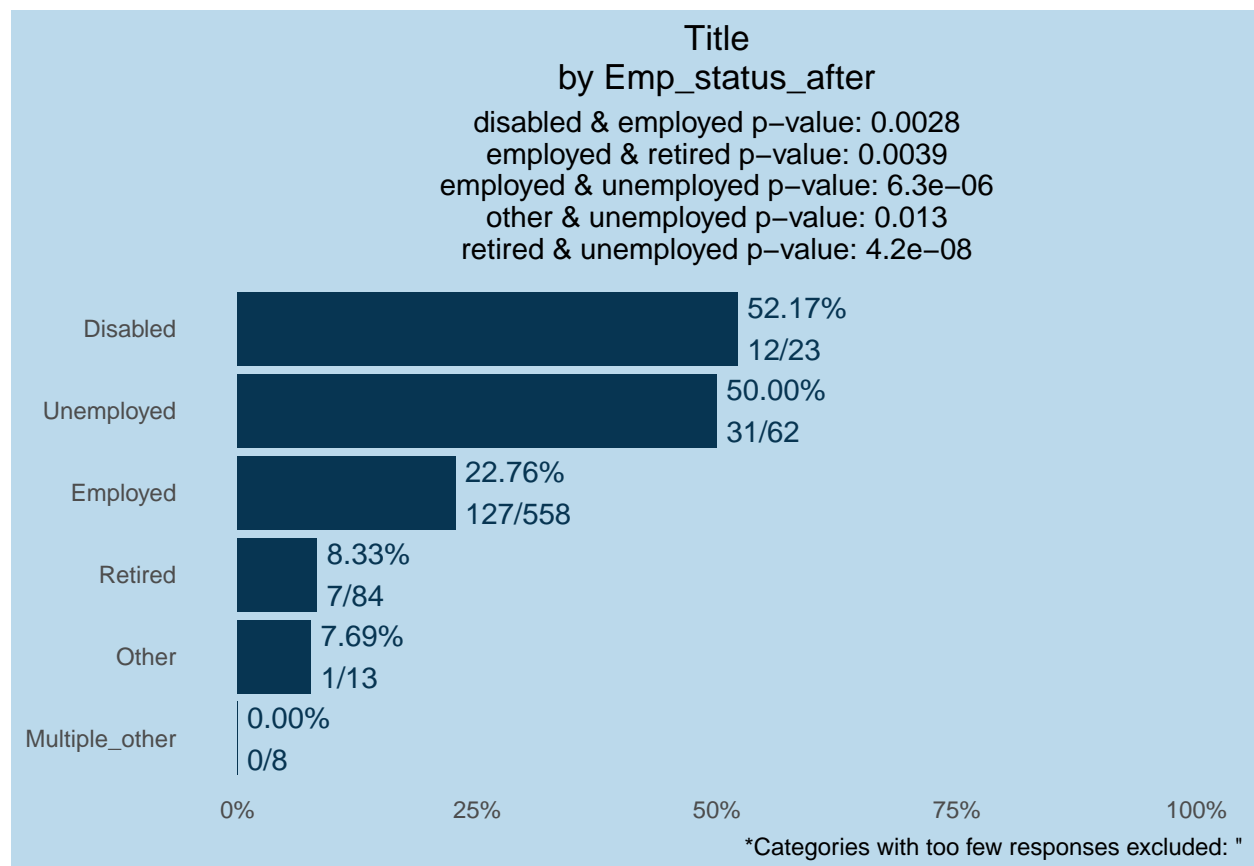
```
##  
## $inc_dist
```



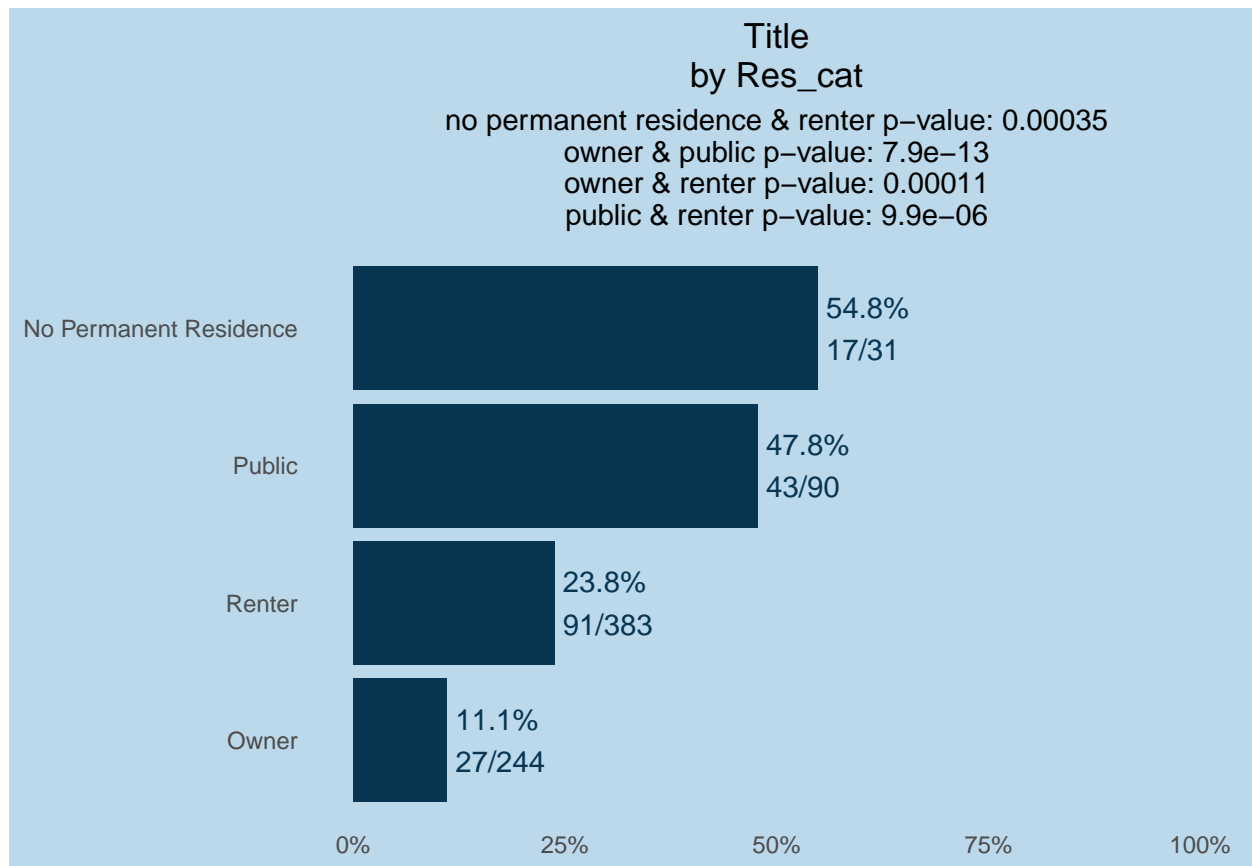
```
##  
## $emp_status_before
```



```
##  
## $emp_status_after
```



```
##
## $res_cat
```



2.10) Households with children were more likely to experience food insecurity in the past year [24,20]

Find respondents who had at least one child (child under 4 or school-aged child) [24] Find proportion of subset who are considered food insecure [20] (use binary definition above) Find proportion not in subset who are considered food insecure and compare (test unequal proportions)

Findings (statistically significant finding)

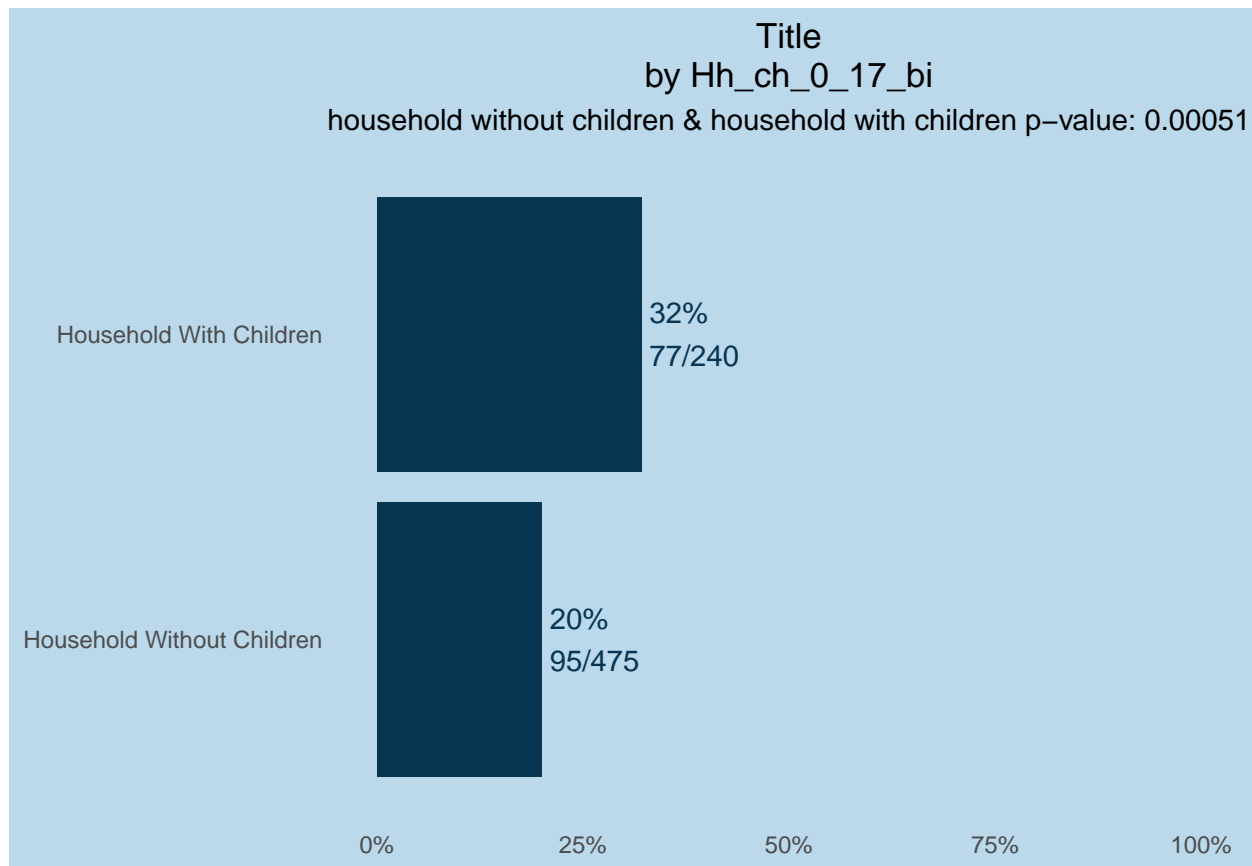
Reiterates findings in previous hypothesis. Families with children experienced more food insecurity than families without.

```
mean(wrangled$hh_ch_0_17_bi == 1 & wrangled$food_insec == 1, na.rm = TRUE)
```

```
## [1] 0.07468477
```

```
make_plots(wrangled, "hh_ch_0_17_bi", hyp_var = "food_insec")
```

```
## $hh_ch_0_17_bi
```



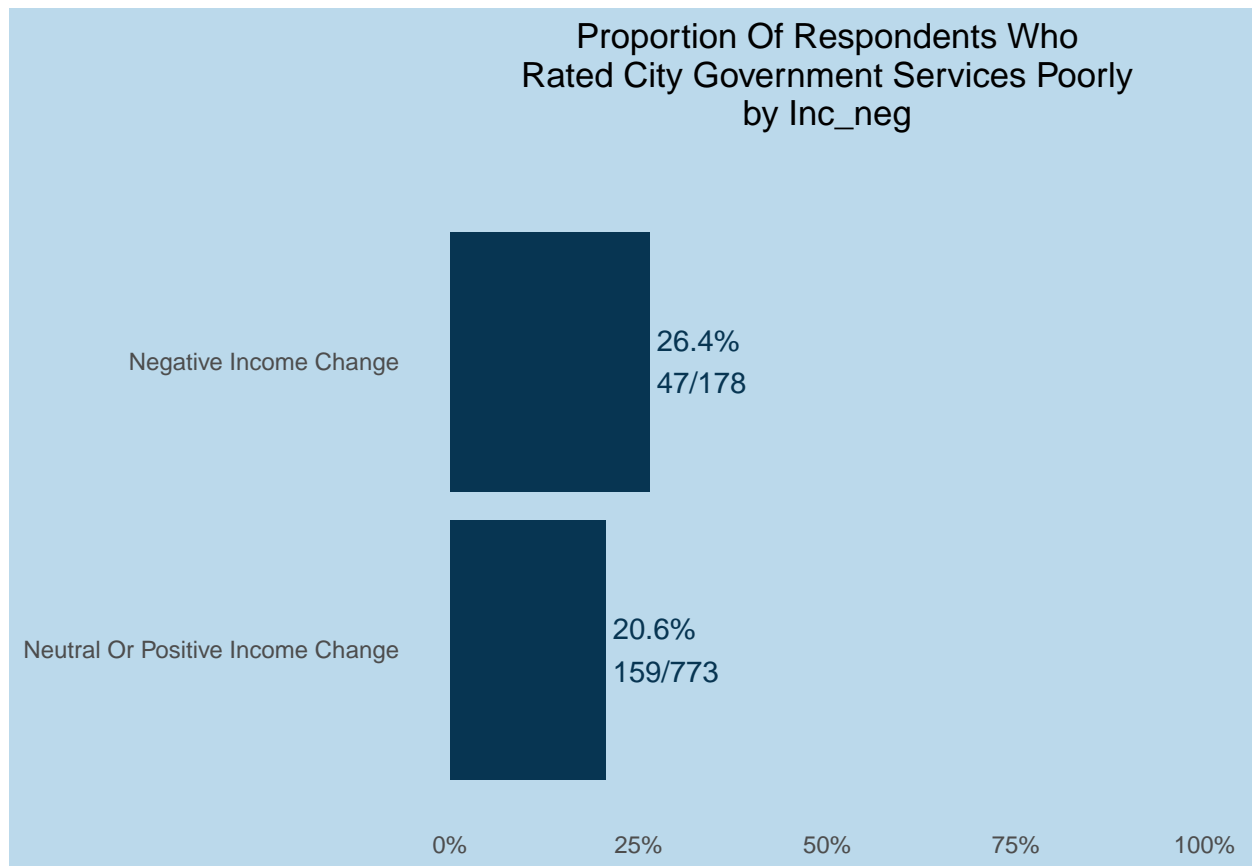
2.11) Respondents who experienced a reduced income were more likely to rate government response poorly [12 & 13]

Run binary distribution over rating government response question Poor=Poor or Very Poor Not Poor=Good, Excellent, Average Find proportion which rated government services poorly [31] Poorly=Poor or Very Poor Find subset of population who witnessed a reduced income Compare with others who did not

Findings (No statistically significant result)

```
make_plots(wrangled,
            by_vars = "inc_neg", hyp_var = "rate_gov_cit_bad", show = "yes",
            title = "Proportion of respondents who\nrated city government services poorly")
```

```
## $inc_neg
```



2.12) Respondents who have a low income (below median income) are more likely to experience violence [12, 13, 34]

Find proportion who faced **discrimination** or violence [34] Find subset who are below median income[13]
Compare and contrast with group who are above median income within the larger proportion

Findings (statistically significant difference on 90% confidence level)

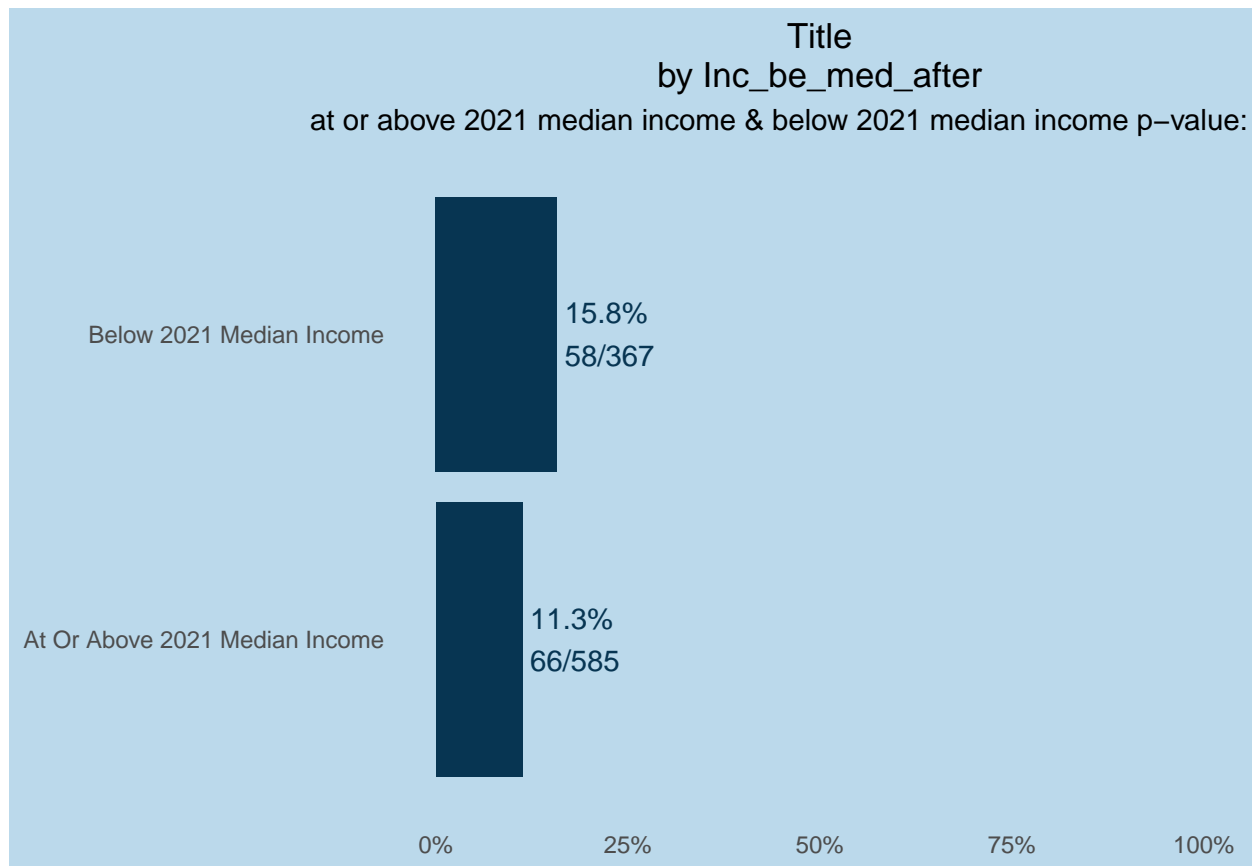
Respondents below median income were more likely to experience violence or abuse. The differing proportions are significant on the 90% confidence level.

```
mean(wrangled$exp_ab_or_vi, na.rm = TRUE)
```

```
## [1] 0.1302521
```

```
make_plots(wrangled, by_vars = "inc_be_med_after", hyp_var = "exp_ab_or_vi")
```

```
## $inc_be_med_after
```

2.13) Respondents who have a low income (below median income) are more likely to be worried about transport while their child attends in-person school

Find proportion who cite transport as one of their concerns when their child [27] Find subset below median income [13] Compare with respondents above median income

Findings (No statistically significant result)

```
make_plots(wrangled %>% filter(hh_ch_0_17_bi == 1), "inc_be_med_after", "con_trans")
```

```
## $inc_be_med_after
## NULL
```