Technical Reference

Outline

\pagebreak

1. About {#about}

DVRPC's IPD analysis identifies populations of interest under Title VI of the Civil Rights Act and the Executive Order on Environmental Justice (#12898) using 2013-2017 American Community Survey (ACS) five-year estimates from the U.S. Census Bureau. IPD analysis assists both DVRPC and outside organizations in equity work by identifying populations of interest, including youth, older adults, female, racial minority, ethnic minority, foreign-born, limited English proficiency, disabled, and low-income populations at the census tract level in DVRPC's nine-county region.

There are many ways of identifying these populations of interest. This document discusses DVRPC's process, which is automated in an `R` script.

1a. Getting started {#one_a}

For guidance on software prerequisites and how to run this script, see `getting_started.pdf` in the `documentation` folder.

1b. Output abbreviations {#one_b}

Components of field names that you'll see in `outputs` and throughout the script.

Component	Equivalent
D	Disabled
EM	Ethnic Minority
F	Female
FB	Foreign-Born
LEP	Limited English Proficiency
LI	Low-Income
OA	Older Adults
RM	Racial Minority
Y	Youth
CntEst	Count Estimate
CntMOE	Count MOE
PctEst	Percentage Estimate
PctMOE	Percentage MOE
Pctile	Percentile
Score	Score
Class	Classification

Abbreviations of field names that you'll see in `outputs` *not* comprised of the above components.

Abbreviation	Equivalent
GEOID	Census Tract Identifier
STATEFP	State FIPS Code
COUNTYFP	County FIPS Code
NAME	Census Tract FIPS Code
IPD_Score	Composite IPD Score

U_TPopEst	Total Population Estimate
U_TPopMOE	Total Population MOE
U_Pop5Est	Population 5+ Estimate
U_Pop5MOE	Population 5+ MOE
U_PPovEst	Poverty Status Population Estimate
U_PPovMOE	Poverty Status Population MOE
U_PNICEst	Non-Institutional Civilian Population Estimate
U_PNICMOE	Non-Institutional Civilian Population MOE

1c. Project structure {#one_c}

This script uses relative file paths based off the location of `ipd.Rproj`. As long as you download the entire repository, the script should have no trouble locating the correct subfolders. All of the subsequent years files are based on the same architecture. The project is structured as follows:

```
ipd
ipd.Rproj
  script.R
    documentation
      discussion.pdf
      getting_started.pdf
      script_reference.pdf
      script_reference.Rmd
      variables.csv
    outputs
      breaks_by_indicator.csv
      counts_by_indicator.csv
      ipd.csv
      ipd.dbf
      ipd.prj
      ipd.shp
      ipd.shx
      mean_by_county.csv
      summary_by_indicator.csv
```

2. Setup {#setup}

2a. Dependencies {#two_a}

Packages required to run this script. If you don't have the packages, you'll get the warning `Error in library (<name of package>) : there is no package called '<name of package>'`, in which case you'll need to install the package before proceeding.

```
library(plyr); library(here); library(sf); library(summarytools);
library(tidycensus); library(tidyverse); library(tigris); library(dplyr);
```

```
library(descr);
```

2b. Fields {#two_b}

The base information we need for IPD analysis are universes, counts, and percentages for nine indicators at the census tract level. For each indicator, the table below shows the indicator name, its abbreviation used in the script, its universe, its count, and its percentage field if applicable. Because the schemata of ACS tables can change with each annual ACS update, these field names are applicable *only* to 2013-2017 ACS Five-Year Estimates.

Some percentage fields are empty. This is okay: we will compute the percentages when they are not directly available from the ACS.

Note that variable B02001_002 ("Estimate; Total: - White alone") is listed as the count for Racial Minority. This is a mathematical shortcut: otherwise, we would need to add several subfields to compute the same estimate. The desired count is B02001_001 (Universe) $-$ B02001_002 ("Estimate; Total: - White alone"). The subtraction is computed after download in Section 5d.i., making a correct estimate and an incorrect MOE. The correct MOE for the count, as calculated in Section 4, will be appended later.

Indicator	**Abbreviation**	**Universe**	**Count**	**Percentage**
Disabled	D	S1810_C01_001	S1810_C02_001	S1810_C03_001
Ethnic Minority	EM	B03002_001	B03002_012	N/A
Female	F	S0101_C01_001	S0101_C05_001	DP05_0003PE
Foreign-Born	FB	B05012_001	B05012_003	N/A
Limited English Proficiency	LEP	S1601_C01_001	S1601_C05_001	S1601_C06_001
Low-Income	LI	S1701_C01_001	S1701_C01_042	N/A
Older Adults	OA	S0101_C01_001	S0101_C01_030	S0101_C02_030
Racial Minority	RM	B02001_001	B02001_002	N/A
Youth	Y	B03002_001	B09001_001	N/A

While it's quicker to embed the names of the desired columns into the code, fields are explicitly spelled out in this script. This is a purposeful design choice. The user should check that the field names point to the correct API request with every IPD update. The best way to check the field names is to visit Census Developers [(link)]() and select the corresponding API. For a history of the ACS variables used in IPD 2015, 2016, and 2017, see `variables.csv` in the `documentation` folder.

| Variable Name | Census Variable | |:----------|:-----------:| | disabled_universe | "S1810_C01_001" | | disabled_count | "S1810_C02_001" | | disabled_percent | "S1810_C03_001" | | ethnic_minority_universe | "B03002_001" | | ethnic_minority_count | "B03002_012" | | ethnic_minority_percent | NA | | female_universe | "S0101_C01_001" | | female_count | "S0101_C05_001" | | female_percent | "DP05_0003PE" | |

foreign_born_universe | "B05012_001" | | foreign_born_count | "B05012_003" | | foreign_born_percent | NA | | limited_english_proficiency_universe | "S1601_C01_001" | limited_english_proficiency_count | "S1601_C05_001" | limited_english_proficiency_percent | "S1601_C06_001" | low_income_universe | "S1701_C01_001" | low_income_count | "S1701_C01_042" | low_income_percent | NA | older_adults_universe | "S0101_C01_001" | older_adults_count | "S0101_C01_030" | older_adults_percent | "S0101_C02_030" | racial_minority_universe | "B02001_001" | racial_minority_count | "B02001_002" | racial_minority_percent | NA | youth_universe | "B03002_001" | youth_count | "B09001_001" | youth_percent | NA

2c. Year {#two_c}

The data download year.

```
ipd_year <- 2017
```

2d. States {#two_d}

The data download state or states. Use the two-character text abbreviation.

```
ipd_states <- c("NJ", "PA")
```

2e. Counties {#two_e}

The counties in your study area. Use five-digit characters concatenating the two-digit state and three-digit county FIPS codes.

```
ipd_counties <- c("34005", "34007", "34015", "34021",
                  "42017", "42029", "42045", "42091", "42101")
```

2f. Census API Key {#two_f}

Placeholder if you have never installed an API key before. If this is your first time accessing the Census API using `R`, see `getting_started.pdf` in the `documentation` folder.

```
# Census API Key
# census_api_key("YOUR API KEY GOES HERE", install = TRUE)
```

THE TYPICAL USER SHOULD NOT HAVE TO EDIT ANYTHING BELOW THIS POINT.

2g. Functions {#two_g}

Load custom functions.

2g.i. Override `base` and `stats` function defaults {#two_g_i}

A time-saver so that it's not required to call `na.rm = TRUE` every time common functions are called.

```
min <- function(i, ..., na.rm = TRUE) {
  base::min(i, ..., na.rm = na.rm)
}
mean <- function(i, ..., na.rm = TRUE) {
  base::mean(i, ..., na.rm = na.rm)
}
sd <- function(i, ..., na.rm = TRUE) {
  stats::sd(i, ..., na.rm = na.rm)
}
max <- function(i, ..., na.rm = TRUE) {
  base::max(i, ..., na.rm = na.rm)
}
```

2g.ii. Create custom half-standard deviation breaks {#two_g_ii}

For a given vector of numbers `x` and a number of bins `i`, `st_dev_breaks` computes the bin breaks starting at $-0.5 \cdot st dev$ and $0.5 \cdot st dev$. For the purposes of IPD analysis, `i = 5`, and `st_dev_breaks` calculates the minimum, $-1.5 \cdot st dev$, $-0.5 \cdot st dev$, $0.5 \cdot st dev$, $1.5 \cdot st dev$, and maximum values. These values are later used to slice the vector into five bins.

2g.iii. *Exception* {#two_g_iii}

All minima are coerced to equal zero. If the first bin break ($-1.5 \cdot st dev$) is negative, as happens when the data has a large spread and therefore a large standard deviation, then this bin break is coerced to equal 0.1. In these cases, only estimates of 0 percent will be placed in the bottom bin.

```
st_dev_breaks <- function(x, i, na.rm = TRUE){
  half_st_dev_count <- c(-1 * rev(seq(1, i, by = 2)),
                         seq(1, i, by = 2))
  if((i %% 2) == 1) {
    half_st_dev_breaks <- sapply(half_st_dev_count,
                                 function(i) (0.5 * i * sd(x)) + mean(x))
    half_st_dev_breaks[[1]] <- 0
    half_st_dev_breaks[[2]] <- ifelse(half_st_dev_breaks[[2]] < 0,
                                      0.1,
                                      half_st_dev_breaks[[2]])
    half_st_dev_breaks[[i + 1]] <- ifelse(max(x) > half_st_dev_breaks[[i + 1]],
                                          max(x), half_st_dev_breaks[[i + 1]])
  } else {
    half_st_dev_breaks <- NA
  }
  return(half_st_dev_breaks)
}
```

2g.iv. Move column or vector of columns to last position {#two_g_iv}

The requested schema for IPD data export renames and places all relevant universes in the final columns of the dataset. `move_last` moves a column or vector of column names to the last position(s) in a data frame.

```
move_last <- function(df, last_col) {
  match(c(setdiff(names(df), last_col), last_col), names(df))
}
```

2g.v. Summarize data {#two_g_v}

`description` tailors the exports from `summarytools::descr` to create summary tables with the requested fields. $0.5 \cdot st dev$ is returned after $stdev$.

```
description <- function(i) {
  des <- as.numeric(descr(i, na.rm = TRUE,
                          stats = c("min", "med", "mean", "sd", "max")))
  des <- c(des[1:4], des[4] / 2, des[5])
  return(des)
}
```

3. Variance replicate table download {#variance_replicate_table_download}

This will feel out of order, but it's necessary. The racial minority indicator is created by summing up several subgroups in ACS Table B03002. This means that the MOE for the count has to be computed. While the ACS has issued guidance on computing the MOE by aggregating subgroups, using the approximation formula can artificially deflate the derived MOE. Variance replicate tables are used instead to account for covariance and compute a more accurate MOE. The MOE computed from variance replicates is substituted in for the racial minority count MOE in Section 5d.ii.

See the Census Bureau's Variance Replicate Tables Documentation [(link)]() for additional guidance on working with variance replicates.

3a. Download variance replicates from Census website {#three_a}

Download, unzip, and read variance replicate tables for Table B02001. Results are combined into a single table called `var_rep`.

```
ipd_states_numeric <- fips_codes %>%
  filter(state %in% ipd_states) %>%
  select(state_code) %>% distinct(.) %>% pull(.)
var_rep <- NULL
for (i in 1:length(ipd_states)){
  url <- paste0("https://www2.census.gov/programs-surveys/acs/replicate_estimates/",
                ipd_year,
                "/data/5-year/140/B02001_",
                ipd_states_numeric[i],
                ".csv.gz")
  temp <- tempfile()
  download.file(url, temp)
```

```
  var_rep_i <- read_csv(gzfile(temp))
  var_rep <- rbind(var_rep, var_rep_i)
}
```

3b. Combine and format downloads {#three_b}

Subset `var_rep` for the study area defined in `ipd_counties` and extract the necessary subgroups.

```
var_rep <- var_rep %>%
  mutate_at(vars(GEOID), funs(str_sub(., 8, 18))) %>%
  filter(str_sub(GEOID, 1, 5) %in% ipd_counties) %>%
  select(-TBLID, -NAME, -ORDER, -moe, -CME, -SE) %>%
  filter(TITLE %in% c("Black or African American alone",
                      "American Indian and Alaska Native alone",
                      "Asian alone",
                      "Native Hawaiian and Other Pacific Islander alone",
                      "Some other race alone",
                      "Two or more races:"))
```

4. Variance replicate table processing {#variance_replicate_table_processing}

4a. Compute racial minority count MOE {#four_a}

Add up the racial minority counts into a single count per census tract for the estimate and 80 variance replicates. Separate the resulting data frame into estimates and variance replicates.

```
num <- var_rep %>%
  group_by(GEOID) %>%
  summarize_if(is.numeric, funs(sum)) %>%
  select(-GEOID)
estim <- num %>% select(estimate)
individual_replicate <- num %>% select(-estimate)
```

Compute the variance replicate for the count. GEOIDs are stored as `id` to be re-appended to the MOEs after they are calculated.

```
id <- var_rep %>% select(GEOID) %>% distinct(.) %>% pull(.)
sqdiff_fun <- function(v, e) (v - e) ^ 2
sqdiff <- mapply(sqdiff_fun, individual_replicate, estim)
sum_sqdiff <- rowSums(sqdiff)
variance <- 0.05 * sum_sqdiff
moe <- round(sqrt(variance) * 1.645, 0)
```

4b. Save results {#four_b}

Save the racial minority MOE.

```
rm_moe <- cbind(id, moe) %>%
  as_tibble(.) %>%
  rename(GEOID10 = id, RM_CntMOE = moe) %>%
  mutate_at(vars(RM_CntMOE), as.numeric)
```

Here are the first few lines of `rm_moe`:

```
head(rm_moe)
```

5. ACS estimates download {#acs_estimates_download}

5a. Fields {#five_a}

Fields for downloads from the ACS API were discussed in Section 2b.

5b. Download counts and universes from Census API {#five_b}

Download counts and percentages for each of IPD's nine indicators. Note that the download is for all census tracts in `ipd_states`.

Input data for IPD comes from ACS Subject Tables, Detailed Tables, and Data Profiles. While one can request all the fields for Subject Tables in one batch, mixing requests for two or more different types of tables will result in failure. For this reason, the counts and universe fields supplied by the user in Section 2b are evaluated for their contents and split into three batches: `s_counts` for Subject Tables, `d_counts` for Detailed Tables, and `dp_counts` for Data Profiles.

The chunk below zips the user-defined calls from the API with the output abbreviations into a data frame called `counts_calls` and separates the calls into three batches.

```
counts <- c(disabled_count, disabled_universe,
            ethnic_minority_count, ethnic_minority_universe,
            female_count, female_universe,
            foreign_born_count, foreign_born_universe,
            limited_english_proficiency_count, limited_english_proficiency_universe,
            low_income_count, low_income_universe,
            older_adults_count, older_adults_universe,
            racial_minority_count, racial_minority_universe,
            youth_count, youth_universe)
counts_ids <- c("D_C", "D_U", "EM_C", "EM_U", "F_C", "F_U",
                "FB_C", "FB_U", "LEP_C", "LEP_U", "LI_C", "LI_U",
                "OA_C", "OA_U", "RM_C", "RM_U", "Y_C", "Y_U")
counts_calls <- tibble(id = counts_ids, api = counts) %>%
  drop_na(.)
s_calls <- counts_calls %>%
  filter(str_sub(api, 1, 1) == "S")
d_calls <- counts_calls %>%
  filter(str_sub(api, 1, 1) == "B")
```

```
dp_calls <- counts_calls %>%
  filter(str_sub(api, 1, 1) == "D")
```

API calls are made separately for ACS Subject Tables, Detailed Tables, and Data Profiles and appended to `dl_counts`. Sometimes there are no requests for an ACS table type; in these situations, the script bypasses a download attempt. Then, information from `counts_calls` is used to rename the downloads to the appropriate abbreviation.

```
dl_counts <- NULL
if(length(s_calls$id > 0)){
  s_counts <- get_acs(geography = "tract",
                      state = ipd_states,
                      output = "wide",
                      year = ipd_year,
                      variables = s_calls$api) %>%
    select(-NAME)
  dl_counts <- bind_cols(dl_counts, s_counts)
}
if(length(d_calls$id > 0)){
  d_counts <- get_acs(geography = "tract",
                      state = ipd_states,
                      output = "wide",
                      year = ipd_year,
                      variables = d_calls$api) %>%
    select(-NAME)
  dl_counts <- left_join(dl_counts, d_counts)
}
if(length(dp_calls$id > 0)){
  dp_counts <- get_acs(geography = "tract",
                       state = ipd_states,
                       output = "wide",
                       year = ipd_year,
                       variables = dp_calls$api) %>%
    select(-NAME)
  dl_counts <- left_join(dl_counts, dp_counts)
}
counts_calls$api <- str_replace(counts_calls$api, "E$", "")
for(i in 1:length(counts_calls$id)){
  names(dl_counts) <- str_replace(names(dl_counts),
                                  counts_calls$api[i],
                                  counts_calls$id[i])
}
dl_counts <- dl_counts %>%
  rename(GEOID10 = GEOID)
```

5b.i. *Exception* {#five_b_i}

The API does not allow redundant downloads, so universes for Older Adults and Youth are duplicated after download. `duplicate_cols` identifies duplicate API calls, and `combined_rows` serves as a crosswalk to duplicate and rename fields.

```
duplicate_cols <- counts_calls %>%
  group_by(api) %>%
```

```
  filter(n()>1) %>%
  summarize(orig = id[1],
            duplicator = id[2])
e_paste <- function(i) paste0(i, "E")
m_paste <- function(i) paste0(i, "M")
e_rows <- apply(duplicate_cols, 2, e_paste)
m_rows <- apply(duplicate_cols, 2, m_paste)
combined_rows <- as_tibble(rbind(e_rows, m_rows)) %>%
  mutate_all(as.character)
for(i in 1:length(combined_rows$api)){
  dl_counts[combined_rows$duplicator[i]] <- dl_counts[combined_rows$orig[i]]
}
```

5c. Download percentages from Census API {#five_c}

Download percentage tables that are available for four of IPD's nine indicators. We will compute percentages and their associated MOEs for the rest of the dataset later. The procedure is identical to that described in Section 5b.

```
percs <- c(disabled_percent,
           ethnic_minority_percent,
           female_percent,
           foreign_born_percent,
           limited_english_proficiency_percent,
           low_income_percent,
           older_adults_percent,
           racial_minority_percent,
           youth_percent)
percs_ids <- c("D_P", "EM_P", "F_P", "FB_P", "LEP_P",
               "LI_P", "OA_P", "RM_P", "Y_P")
percs_calls <- tibble(id = percs_ids, api = percs) %>%
  drop_na(.)
s_calls <- percs_calls %>%
  filter(str_sub(api, 1, 1) == "S")
d_calls <- percs_calls %>%
  filter(str_sub(api, 1, 1) == "B")
dp_calls <- percs_calls %>%
  filter(str_sub(api, 1, 1) == "D")
dl_percs <- NULL
if(length(s_calls$id > 0)){
  s_percs <- get_acs(geography = "tract",
                     state = ipd_states,
                     output = "wide",
                     year = ipd_year,
                     variables = s_calls$api) %>%
    select(-NAME)
  dl_percs <- bind_cols(dl_percs, s_percs)
}
if(length(d_calls$id > 0)){
  d_percs <- get_acs(geography = "tract",
                     state = ipd_states,
                     output = "wide",
```

```
                      year = ipd_year,
                      variables = d_calls$api) %>%
     select(-NAME)
   dl_percs <- left_join(dl_percs, d_percs)
 }
 if(length(dp_calls$id > 0)){
   dp_percs <- get_acs(geography = "tract",
                       state = ipd_states,
                       output = "wide",
                       year = ipd_year,
                       variables = dp_calls$api) %>%
     select(-NAME)
   dl_percs <- left_join(dl_percs, dp_percs)
 }
 percs_calls$api <- str_replace(percs_calls$api, "PE", "")
 names(dl_percs) <- str_replace(names(dl_percs), "PE", "E")
 names(dl_percs) <- str_replace(names(dl_percs), "PM", "M")
 for(i in 1:length(percs_calls$id)){
   names(dl_percs) <- str_replace(names(dl_percs),
                                  percs_calls$api[i],
                                  percs_calls$id[i])
 }
 dl_percs <- dl_percs %>%
   rename(GEOID10 = GEOID)
```

5d. Format downloads {#five_d}

Subset `dl_counts` and `dl_percs` for DVRPC's nine-county region. Percentages should range from 0 to 100.

```
dl_counts <- dl_counts %>%
  filter(str_sub(GEOID10, 1, 5) %in% ipd_counties)
dl_percs <- dl_percs %>%
  filter(str_sub(GEOID10, 1, 5) %in% ipd_counties)
```

5d.i. *Exception* {#five_d_i}

Note that variable B02001_002 ("Estimate; Total: - White alone") was downloaded as the count for racial minority. Compute B02001_001 (Universe) $-$ B02001_002 ("Estimate; Total: - White alone") and substitute for `RM_CE`.

```
dl_counts <- dl_counts %>% mutate(x = RM_UE - RM_CE) %>%
  select(-RM_CE) %>%
  rename(RM_CE = x)
```

5d.ii. *Exception* {#five_d_ii}

Before computing percentages and percentage MOEs, import the count MOE for the racial minority variable computed from variance replicates. If `rm_moe` exists, then this chunk will substitute the correct count MOE in `dl_counts`; if not, this chunk will do nothing.

```
if(exists("rm_moe")){
  dl_counts <- dl_counts %>%
    select(-RM_CM) %>%
    left_join(., rm_moe) %>%
    rename(RM_CM = RM_CntMOE) %>%
    mutate_at(vars(RM_CM), as.numeric)
}
```

5d.iii. *Exception* {#five_d_iii}

Half-standard deviations serve as the classification bins for IPD scores, and including zero-population tracts affects computed standard deviation values. Start by removing the 11 census tracts with zero population.

```
slicer <- c("34005981802","34005982200","34021980000","42017980000",
            "42045980300","42045980000","42045980200","42091980100",
            "42091980000","42091980200","42091980300","42101036901",
            "42101980001","42101980002","42101980003","42101980300",
            "42101980701","42101980702","42101980800","42101980100",
            "42101980200", "42101980400","42101980500","42101980600",
            "42101980901","42101980902","42101980903","42101980904",
            "42101980905","42101980906", "42101989100","42101989200",
            "42101989300")
dl_counts <- dl_counts %>% filter(!(GEOID10 %in% slicer))
dl_percs <- dl_percs %>% filter(!(GEOID10 %in% slicer))
```

Here are the first few lines of `dl_counts` and `dl_percs`. Notice the naming convention:

- `UE` = universe estimate
- `UM` = universe MOE
- `CE` = count estimate
- `CM` = count MOE
- `PE` = percentage estimate
- `PM` = percentage MOE

We use these strings to select columns, so consistency is key.

```
head(dl_counts)
head(dl_percs)
```

6. ACS estimates calculations {#acs_estimates_calculations}

For all nine indicators, this section computes:

a. Percentages and percentage MOEs b. Percentile c. IPD score and classification d. Composite IPD score

Split `dl_counts` into a list named `comp` for processing and arrange column names in alphabetical order. The name of the list, `comp`, is a nod to the "component parts" of `dl_counts`. The structure of `comp` is similar to a four-tab Excel spreadsheet: for example, `comp` is the name of the `.xlsx` file, `uni_est` is a tab for universe estimates, and `uni_est` has nine columns and 1,368 rows, where the column is the IPD indicator and the row is the census tract observation.

The order of columns is important because processing is based on vector position. We want to make sure that the first column of every tab corresponds to the Disabled indicator, the second to Ethnic Minority, et cetera.

```
comp <- list()
comp$uni_est <- dl_counts %>% select(ends_with("UE")) %>% select(sort(current_vars()))
comp$uni_moe <- dl_counts %>% select(ends_with("UM")) %>% select(sort(current_vars()))
comp$count_est <- dl_counts %>% select(ends_with("CE")) %>%
select(sort(current_vars()))
comp$count_moe <- dl_counts %>% select(ends_with("CM")) %>%
select(sort(current_vars()))
```

6a. Percentages and percentage MOEs {#six_a}

6a.i. Calculation {#six_a_i}

MOEs of the percentage values are obtained using the `tidycensus` function `moe_prop`. This chunk mentions `r` and `c` several times: continuing the spreadsheet analogy, think of `r` as the row number and `c` as the column number for a given spreadsheet tab.

```
pct_matrix <- NULL
pct_moe_matrix <- NULL
for (c in 1:length(comp$uni_est)){
  pct <- unlist(comp$count_est[,c] / comp$uni_est[,c])
  pct_matrix <- cbind(pct_matrix, pct)
  moe <- NULL
  for (r in 1:length(comp$uni_est$LI_UE)){
    moe_indiv <- as.numeric(moe_prop(comp$count_est[r,c],
                                     comp$uni_est[r,c],
                                     comp$count_moe[r,c],
                                     comp$uni_moe[r,c]))
    moe <- append(moe, moe_indiv)
  }
  pct_moe_matrix <- cbind(pct_moe_matrix, moe)
}
```

6a.ii. Result {#six_a_ii}

`pct` and `pct_moe` stores the percentages and associated MOEs for the nine indicator variables. Results are rounded to the tenths place and range from 0 to 100.

```
pct <- as_tibble(pct_matrix) %>% mutate_all(funs(. * 100)) %>% mutate_all(round, 1)
names(pct) <- str_replace(names(comp$uni_est), "_UE", "_PctEst")
pct_moe <- as_tibble(pct_moe_matrix) %>% mutate_all(funs(. * 100)) %>%
mutate_all(round, 1)
names(pct_moe) <- str_replace(names(comp$uni_est), "_UE", "_PctMOE")
```

6a.iii. *Exception* {#six_a_iii}

If the percentage MOE equals 0, then overwrite it to equal 0.1. This should be a rare occurence with survey data at the census tract level.

```
pct_moe <- pct_moe %>% replace(., . == 0, 0.1)
```

6a.iv. ***Exception*** {#six_a_iv}

Substitute percentages and associated MOEs when available. This applies to the older adults, female, limited English proficiency, and disabled variables.

```
pct <- pct %>% mutate(D_PctEst = dl_percs$D_PE,
                      OA_PctEst = dl_percs$OA_PE,
                      LEP_PctEst = dl_percs$LEP_PE,
                      F_PctEst = dl_percs$F_PE)
pct_moe <- pct_moe %>% mutate(D_PctMOE = dl_percs$D_PM,
                              OA_PctMOE = dl_percs$OA_PM,
                              LEP_PctMOE = dl_percs$LEP_PM,
                              F_PctMOE = dl_percs$F_PM)
```

Here are the first few lines of `pct` and `pct_moe`:

```
head(pct)
head(pct_moe)
```

6b. Percentile {#six_b}

6b.i. Calculation {#six__b_i}

Add percentiles (an additional "spreadsheet tab") to `comp`, making sure to first sort column names alphabetically. Compute the empirical cumulative distribution function for each of the nine indicator variables. The ECDF can range from 0 to 1, where 1 indicates the largest observed percentage.

```
comp$pct_est <- pct %>% select(sort(current_vars()))
percentile_matrix <- NULL
for (c in 1:length(comp$uni_est)){
  p <- unlist(comp$pct_est[,c])
  rank <- ecdf(p)(p)
  percentile_matrix <- cbind(percentile_matrix, rank)
}
```

6b.ii. Result {#six_b_ii}

`percentile` stores the percentile for the nine indicator variables. Results are rounded to the hundredths place.

```
percentile <- as_tibble(percentile_matrix) %>% mutate_all(round, 2)
names(percentile) <- str_replace(names(comp$uni_est), "_UE", "_Pctile")
```

Here are the first few lines of `percentile`:

```
head(percentile)
```

6c. IPD score and classification {#six_c}

Each observation is assigned an IPD score for each indicator. The IPD score for an individual indicator can range from 0 to 4, which corresponds to the following classification and bin breaks:

IPD Score	IPD Classification	Standard Deviations
0	Well Below Average	x $< -1.5 \cdot stdev$
1	Below Average	$-1.5 \cdot stdev \leq$ x $<-0.5 \cdot stdev$
2	Average	$-0.5 \cdot stdev \leq$ x $<0.5 \cdot stdev$
3	Above Average	$0.5 \cdot stdev \leq$ x $<1.5 \cdot stdev$
4	Well Above Average	x $\geq 1.5 \cdot stdev$

6c.i. Calculation {#six_c_i}

The function `st_dev_breaks` is called to compute the bin breaks for each indicator. These breaks determine the IPD score stored in `score`. Note that we divide *rounded* `PctEst` columns by *unrounded* half-standard deviation breaks to compute the `score`. `class` is a textual explanation of the IPD score.

```
score_matrix <- NULL
class_matrix <- NULL
for (c in 1:length(comp$uni_est)){
  p <- unlist(comp$pct_est[,c])
  breaks <- st_dev_breaks(p, 5, na.rm = TRUE)
  score <- case_when(p < breaks[2] ~ 0,
                     p >= breaks[2] & p < breaks[3] ~ 1,
                     p >= breaks[3] & p < breaks[4] ~ 2,
                     p >= breaks[4] & p < breaks[5] ~ 3,
                     p >= breaks[5] ~ 4)
  class <- case_when(score == 0 ~ "Well Below Average",
                     score == 1 ~ "Below Average",
                     score == 2 ~ "Average",
                     score == 3 ~ "Above Average",
                     score == 4 ~ "Well Above Average")
  score_matrix <- cbind(score_matrix, score)
  class_matrix <- cbind(class_matrix, class)
}
```

6c.ii. Result {#six_c_ii}

`score` and `class` store the IPD scores and associated descriptions for the nine indicator variables.

```
score <- as_tibble(score_matrix)
names(score) <- str_replace(names(comp$uni_est), "_UE", "_Score")
```

```
class <- as_tibble(class_matrix)
names(class) <- str_replace(names(comp$uni_est), "_UE", "_Class")
```

Here are the first few lines of `score` and `class`:

```
head(score)
head(class)
```

6d. Composite IPD score {#six_d}

6d.i. Calculation {#six_d_i}

Sum the IPD scores for the nine indicator variables to determine the composite IPD score.

```
score <- score %>% mutate(IPD_Score = rowSums(.))
```

6d.ii. Result {#six_d_ii}

Here are the first few records of the composite IPD score:

```
head(score$IPD_Score)
```

7. ACS estimates cleaning {#acs_estimates_cleaning}

There is a specific output format for `ipd.csv`, including column names, column order, flags for missing data, and census tracts with insufficient data. This section ensures conformity with the output formatting.

Merge the percentage estimates, percentage MOEs, percentile, score, and class data frames into a single data frame called `ipd`.

```
ipd <- bind_cols(dl_counts, pct) %>%
  bind_cols(., pct_moe) %>%
  bind_cols(., percentile) %>%
  bind_cols(., score) %>%
  bind_cols(., class)
```

Rename columns.

```
names(ipd) <- str_replace(names(ipd), "_CE", "_CntEst")
names(ipd) <- str_replace(names(ipd), "_CM", "_CntMOE")
ipd <- ipd %>% mutate(STATEFP10 = str_sub(GEOID10, 1, 2),
                      COUNTYFP10 = str_sub(GEOID10, 3, 5),
                      NAME10 = str_sub(GEOID10, 6, 11),
                      U_TPopEst = F_UE,
                      U_TPopMOE = F_UM,
                      U_Pop5Est = LEP_UE,
                      U_Pop5MOE = LEP_UM,
                      U_PPovEst = LI_UE,
```

```
                       U_PPovMOE = LI_UM,
                       U_PNICEst = D_UE,
                       U_PNICMOE = D_UM) %>%
  select(-ends_with("UE"), -ends_with("UM"))
```

Reorder columns, with `GEOID` and FIPS codes first, the following variables in alphabetical order, and the total IPD score and universes at the end.

```
ipd <- ipd %>% select(GEOID10, STATEFP10, COUNTYFP10, NAME10, sort(current_vars()))
%>%
  select(move_last(., c("IPD_Score", "U_TPopEst", "U_TPopMOE",
                        "U_Pop5Est", "U_Pop5MOE", "U_PPovEst",
                        "U_PPovMOE", "U_PNICEst", "U_PNICMOE")))
```

At the beginning of processing, we removed 11 census tracts from processing because their populations were equal to zero. Tack these back on to the dataset.

```
slicer <- enframe(slicer, name = NULL, value = "GEOID10")
ipd <- plyr::rbind.fill(ipd, slicer)
```

Replace `NA` values with `NoData` if character and `-99999` if numeric.

```
ipd <- ipd %>% mutate_if(is.character, funs(ifelse(is.na(.), "NoData", .))) %>%
  mutate_if(is.numeric, funs(ifelse(is.na(.), -99999, .)))
```

8. Summary Tables {#summary_tables}

This section generates a handful of other deliverables, including:

a. Counts by indicator b. Breaks by indicator c. Summary by indicator d. County means by indicator

Replace `-99999` with `NA` for numeric columns to avoid distorting summary statistics.

```
ipd_summary <- ipd
ipd_summary[ipd_summary == -99999] <- NA
```

8a. Counts by indicator {#eight_a}

The number of census tracts that fall in each bin. Count census tracts by indicator and bin. Reorder factor levels so that "Well Below Average" appears before "Below Average," and the like.

```
counts <- ipd_summary %>% select(ends_with("Class"))
export_counts <- apply(counts, 2, function(i) plyr::count(i))
for(i in 1:length(export_counts)){
  export_counts[[i]]$var <- names(export_counts)[i]
}
export_counts <- map_dfr(export_counts, `[`, c("var", "x", "freq"))
colnames(export_counts) <- c("Variable", "Classification", "Count")
export_counts$Classification <- factor(export_counts$Classification,
                                       levels = c("Well Below Average",
```

```
                                                    "Below Average",
                                                    "Average",
                                                    "Above Average",
                                                    "Well Above Average",
                                                    "NoData"))
export_counts <- arrange(export_counts, Variable, Classification)
export_counts <- export_counts %>%
  spread(Classification, Count) %>%
  mutate_all(funs(replace_na(., 0))) %>%
  mutate(TOTAL = rowSums(.[2:7], na.rm = TRUE))
```

8b. Breaks by indicator {#eight_b}

The bin breaks for each indicator. Apply the `st_dev_breaks` function to all percentage values and export results.

```
breaks <- ipd_summary %>% select(ends_with("PctEst"))
export_breaks <- round(mapply(st_dev_breaks, x = breaks, i = 5, na.rm = TRUE), digits
= 3)
export_breaks <- as_tibble(export_breaks) %>%
  mutate(Class = c("Min", "1", "2", "3", "4", "Max")) %>%
  select(Class, current_vars())
```

8c. Summary by indicator {#eight_c}

Summary statistics of each indicator. Round results to two decimal places.

```
pcts <- ipd_summary %>% select(ends_with("PctEst"))
summary_data <- apply(pcts, 2, description)
export_summary <- as_tibble(summary_data) %>%
  mutate_all(round, 2) %>%
  mutate(Statistic = c("Minimum", "Median", "Mean", "SD", "Half-SD", "Maximum")) %>%
  select(Statistic, current_vars())
```

8d. County means by indicator {#eight_d}

Population-weighted means by county and indicator. For the most accurate percentage values, aggregate all counts back to the county level and compute percentages. In the export file, counties are referred to by the five-digit character supplied by the user to `ipd_counties`.

```
export_means <- dl_counts %>% select(GEOID10, ends_with("UE"), ends_with("CE")) %>%
  select(GEOID10, sort(current_vars())) %>%
  mutate(County = str_sub(GEOID10, 1, 5)) %>%
  select(-GEOID10) %>%
  group_by(County) %>%
  summarize(D_PctEst = sum(D_CE) / sum(D_UE),
            EM_PctEst = sum(EM_CE) / sum(EM_UE),
            F_PctEst = sum(F_CE) / sum(F_UE),
            FB_PctEst = sum(FB_CE) / sum(FB_UE),
            LEP_PctEst = sum(LEP_CE) / sum(LEP_UE),
            LI_PctEst = sum(LI_CE) / sum(LI_UE),
```

```
            OA_PctEst = sum(OA_CE) / sum(OA_UE),
            RM_PctEst = sum(RM_CE) / sum(RM_UE),
            Y_PctEst = sum(Y_CE) / sum(Y_UE)) %>%
  mutate_if(is.numeric, funs(. * 100)) %>%
  mutate_if(is.numeric, round, 1)
```

9. Export {#export}

9a. Append to TIGER/LINE file {#nine_a}

Using the arguments supplied in `ipd_county`, download the relevant census tracts and append `ipd` to them. Uncommenting `cb = TRUE` will greatly speed processing time by downloading generalized tract boundary shapefiles instead of detailed ones.

```
options(tigris_use_cache = TRUE, tigris_class = "sf")
st <- str_sub(ipd_counties, 1, 2)
cty <- str_sub(ipd_counties, 3, 5)
trct <- map2(st, cty, ~{tracts(state = .x,
                               county = .y,
                               #cb = TRUE,
                               year = ipd_year)}) %>%
  rbind_tigris() %>%
  st_transform(., 26918) %>%
  select(GEOID) %>%
  left_join(., ipd, by = c("GEOID" = "GEOID10")) %>%
  rename(GEOID10 = GEOID)
```

9b. Export files {#nine_b}

Results are saved in `outputs`.

```
st_write(trct, here("outputs", "ipd.shp"), delete_dsn = TRUE, quiet = TRUE)
write_csv(ipd, here("outputs", "ipd.csv"))
write_csv(export_counts, here("outputs", "counts_by_indicator.csv"))
write_csv(export_breaks, here("outputs", "breaks_by_indicator.csv"))
write_csv(export_summary, here("outputs", "summary_by_indicator.csv"))
write_csv(export_means, here("outputs", "mean_by_county.csv"))
```