Armenia CCDR Microsimulation

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0.1 Introduction

In this calculation file, we "age" the household survey according to demographic projections and different macroeconomic scenarios to explore the impact of climate-related risks and policy measures on the consumption expenditure distribution. It is part of a larger project with all contributions to Armenia's CCDR, which can be downloaded from GitHub in the form of an Rstudio project.

As a convention, code is presented in the following format in this guide:

```
# Some comment that is not evaluated by R
some_variable <- some_function(some_object, some_parameter = TRUE)
```

We assume that the reader has created an Rstudio project and is familiar with basic R functions. Within that project we recommend the following file structure:

```
root/
  scripts
     my_script.R
  data/
|      my_data.sav
|      my_data.dta
|      my_data.csv
  output
      my_output1.csv
      my_output2.xlsx
```

Using RStudio project makes it possible to not use `setwd()` to establish the root directory and refer to subdirectories in a relative manner, making interoperability easier within teams and not hard coding a particular computer's file structure into the code. If you are not using RStudio, just add `setwd(r'(C:\My\path\to\project\root)')` at the beginning of your coding session.

0.2 Preamble

We start with a clean environment, making sure that any objects from a previous session are not present. We take this opportunity to keep our country ISO code in a variable `iso` in case we need it later.

```
# Clean workspace
rm(list = ls())

# Armenia country ISO code
iso <- "ARM"

# Survey year
```

```
surveyyear <- 2022

# Exchange rate USD per dram
er <- 0.002310
```

We call the appropriate libraries.

Rather than calling our libraries as we go, we will make sure we have everything we need from the beginning.

```
library(tidyverse) # includes dplyr, ggplot2 and others
library(haven)     # to read SPSS and Stata datasets
library(readxl)    # to read from MS-Excel
library(openxlsx)  # to write to MS-Excel.
library(gt)        # pretty tables
library(car)       # companion to applied regression
library(modelr)    # regression models
#library(anesrake)
# Raking reweighting but we don't load it, because
# it changes the meaning of summarize from dplyr,
# so we use the form anesrake::anesrake() when using it.
#library(ebal)      # Entropy reweighting (not used)
library(janitor)   # pretty subtotals
library(broom)     # More regressions
library(purrr)     # map vectors (aggregation)
library(zoo)       # Calculate moving window average and max value

# Geopackages
library(sf)        # to read and write shapefile maps
library(terra)     # to perform geocalculations
library(tmap)      # for static and interactive maps
```

0.3 Datasets

We then load the datasets that we need for this study. The World Bank has processed some of these already for poverty analysis and so we have the original SPSS datasets with all variables for Households `hh` and for Individuals `pp`, as well as a consumption aggregate `ca` and a household income `ic` dataset, which are Stata datasets. This is for the year 2022. These are imported using the `haven` package. These are based on Armenia Integrated Living Conditions Survey 2022 (ARMSTAT, 2023).

```r
# Households (hh)
hh <- read_sav(
  "data/ARM-HH-survey/original-spss-files/ILCS-ARM-2022-Households.sav")
# Persons (pp)
pp <- read_sav(
  "data/ARM-HH-survey/original-spss-files/ILCS-ARM-2022-Persons.sav")
# Consumption aggregate at household level (ca)
ca  <- read_dta("data/ARM-HH-survey/CONSAGG2022.dta")
# Processed income at household level (ic)
ic  <- read_dta("data/ARM-HH-survey/totinc.dta")
# Food diary
food_with_prices <- read_dta("data/ARM-HH-survey/FOOD_with_prices_short.dta")
```

We will work non-destructively, meaning we will not rewrite these data sets and we will only create intermediate data frame objects from them to perform transformations, selections and other data management tasks. For example, we will keep household assignment to poverty status and consumption deciles handy by creating a subset of our `ca` data with only our household identifiers, deciles, and poverty.

```r
# From the WB processed dataset, we extract deciles and poverty
deciles <- ca %>%
  select( hhid, decile, poor_Avpovln2022,
          poor_Foodpovln2022, poor_Lpovln2022, poor_Upovln2022)
```

Our population data comes from UN's projections.

```r
population_projections <- read_dta("data/UN2022_population.dta") %>%
  filter(country == iso) # we filter for Armenia
```

The macro scenario dataset is an input provided by the Macroeconomic CGE simulation team, with yearly information on GDP, working age population, employment by economic activity (for an aggregation of three sectors: agriculture, manufacturing, and services), wages by economic activity, value added by economic activity, remittances, consumer price index, food price index and energy price index (for a bundle of gas, oil, coal, electricity) by decile (10 representative households in the macro model), and carbon tax revenue transfers to household deciles.

```r
scenario_file <- "data/ARM-Microsimulation/ARM_MacroScenarioInformation.xlsx"
scenario_varlist <- read_xlsx(
  "data/ARM-Microsimulation/ARM_Macro_varlist.xlsx")
prices_2030 <-
  read.csv("data/ARM-Microsimulation/prices2030.csv")
```

Economic Activities in the Survey is in Armenian. The following dataset is a lookup table with the English names.

```r
sectors <- read_xlsx("data/ARM-HH-survey/economic_activity_codes.xlsx")
```

We also have geographical information for level 1 in Shapefile format, which we import with the `sf` package. We rename the column with the name of the administrative region to match our household survey data set conventions to ease mergers. The `dplyr` package from the `tidyverse` meta package allows us to "pipe" or link processing steps using the `%>%` pipe. Although there is no geoprocessing in this analysis, this will come in handy for graphical presentations.

```r
# Armenia marzes or administrative level 1 shapefile
adm1 <- read_sf("data/ARM-Geodata/ARM-ADM1.shp") %>%
  select(NAM_1, COD_HH_SVY, geometry) %>%
  # Make sure that names match the rest of datasets
  mutate(NAM_1 = if_else(NAM_1 == "Gergharkunik", "Gegharkunik", NAM_1))
# We rename with the survey designation
names(adm1)[2] <- "hh_02"
```

And we plot it for reference (see Figure 1). This is done with the tmap R package and the code shown in Listing 1.

Listing 1 Plotting a map with with the tmap package

```r
tm_shape(adm1)+
  tm_polygons("NAM_1", legend.show = FALSE) +
  tm_text("NAM_1", size = 3/4)
```

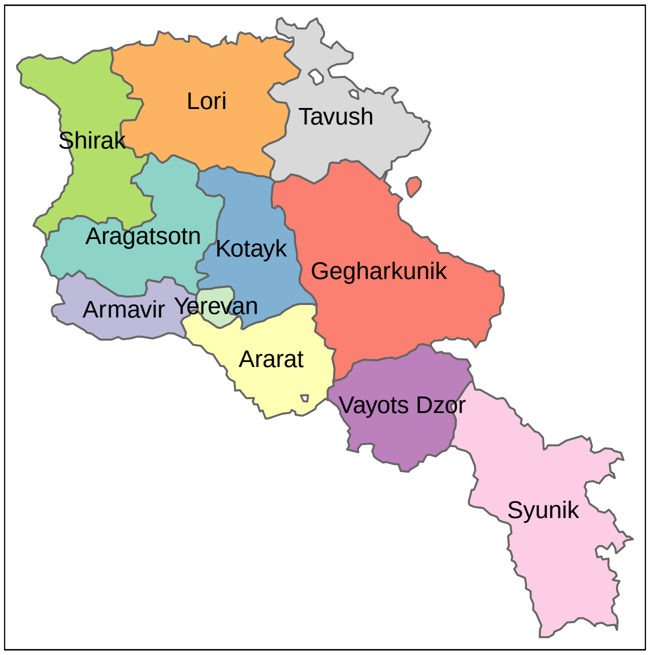


Figure 1: Map of Armenia at administrative level 1 (ADM1)

Marzes names are more accurate in the shapefile than in the survey. We will use them from here on instead of the survey factor labels.

Listing 2 Marz name from geodata

```
hh <- hh %>%
  left_join(adm1, join_by(hh_02 == hh_02)) %>%
  select(-geometry)

ic <- ic %>%
  left_join(adm1, join_by(hh_02 == hh_02)) %>%
  select(-geometry)
```

We also have an Excel file with changes to labor productivity due to climate variability. We bind together the datasets found in each Excel sheet.

Finally, we have our climate vulnerability information. For this analysis we only use the `crops_productivity` and `livestock_productivity` that comes from *Estimating the Economic Impacts of Climate Change in Armenia* (Strzepek, Boehlert, Castillo, & Smet, 2024).

Listing 3 Import labor productivity data

```
file <- r"(data/ARM-Microsimulation/LaborProductivityChanges.xlsx)"
sheets <- excel_sheets(file)

# Use lapply to read and process each sheet
labor_productivity <- lapply(sheets, function(sheet) {
  info <- read_excel(
    file,
    sheet = sheet,
    col_names = TRUE,
    col_types = c("text", "text", "numeric", "text", "numeric")
  )
  info$sector <- sheet
  return(info)
})

# Bind all data frames in the list into a single data frame
labor_productivity <- bind_rows(labor_productivity)
```

0.4 Data preparation income outliers and missings

0.4.1 Household consumption aggregates and characteristics

Initial necessary variables. Some of these choices come from conventions used in the guidance code. However, where possible, we've tried to continue using the names found in the datasets to avoid introducing more confusion.

```
consumption_aggregates <- ca %>%
  mutate(rural = ifelse(urb_rur == 2, 1, 0),  # Create rural indicator
         yhh = totc,               # Total household expenditure
         wgt_adj = pweight) %>%        # Make a copy of the weight variable
  select(hhid, rural, hhsize,hhsize_R, marz, aepc, yhh, wgt_adj, weight,
         Foodpovln2022, Lpovln2022, Upovln2022, Avpovln2022,
         poor_Foodpovln2022, poor_Lpovln2022, poor_Upovln2022,
         poor_Avpovln2022, decile )  # Keep only necessary columns
```

Listing 4 Import crops and livestock yield loss data

```
crops_productivity <-
  read.csv("data/ARM-Vulnerability-Analysis/ARM_crops_combined_REF_shock_admin1.csv") %>%
  rename(NAM_1 = Province)
livestock_productivity <-
  read.csv(
    "data/ARM-Vulnerability-Analysis/ARM_livestock_REF_shock_admin1.csv"
    ) %>%
  rename(NAM_1 = Province)
```

0.4.2 Demographic characteristics, education, labor force

Here the original code calls for Zone data, which is not present in our dataset, due to the different administrative structure of Armenia. However, we use `hh_01_code` (settlement) for this purpose. In the end, this variable was never used.

```
zone_data <- hh %>%
  select(interview__key, hh_01_code, hh_02, hh_03, NAM_1) %>%
  rename(
    hhid = interview__key, # Household id
    zone = hh_01_code,     # Settlement
    marz = hh_02,          # Marz
    NAM_1 = NAM_1,         # Marz name
    urb_rur = hh_03        # Urban / rural
  )
```

Demographic data, merge with zone data Note that ed_03 (educy) below is not years of education, but education level (primary, general, secondary, etc.) However, it is ordered in a way that higher levels imply more years of education. We perform several steps within the first pipe call. The variable `lstatus` (Labor Force Status) here is very important for the reweigthing of the dataset later on. Note that from here onwards we will be creating `_microsim` versions of our datasets with the transformations needed for calculations. That way we avoid changing our original data and can refer to it later without fearing we've left things behind.

```
pp_microsim <- pp %>%
  rename(hhid = interview__key) %>%
  left_join(zone_data, join_by(hhid == hhid))  %>%
  mutate(
    # Demographic characteristics
    # Unique person id
    pid = paste0(hhid, "-", str_pad(mem_001__id, 2, pad = "0")),
    head = ifelse(mem_03 == 1, 1, 0),
    # Education level
    educy = ifelse(is.na(ed_03) | ed_03 == 8, 0, ed_03),
    # Labor Force Status
    lstatus = case_when(
      # 1. Employed
      est_03 == 1 | est_04 == 1 | est_05 == 1 |
        est_06 == 1 | est_08 == 1 ~ 1L,
      # 2. Unemployed (available, and searching)
      est_10 == 1 ~ 2L,
      # 3. Inactive (available, not searching)
      est_10 == 2 ~ 3L,
      # Out of the labor force
      .default = 4L # Default to OLF
    ),
    employed = (lstatus == 1),
    # Salaried status (1. paid employee; 2 self-employed)
    salaried = ifelse(
      !is.na(emp_11a),
      1L,
      ifelse(is.na(emp_11a) &
               employed == TRUE, 0L, NA_integer_)
    )
  ) %>%
  rename(rel = mem_03, # relationship to HH head
         gender = mem_02,
         age = mem_05)
```

Later, when we conduct the reweighting of the dataset, we need to summarize into three levels of education.

```
pp_microsim <- pp_microsim %>%
  mutate(calif = case_when(
    educy >= 0 & educy <= 2 ~ "None - General",
    educy > 3 & educy <= 7 ~ "Secondary - Vocational",
    educy > 7 & educy <= 11 ~ "Higher +",
    TRUE ~ NA_character_  # Values outside the specified ranges
  ))
```

Count the number of employed persons by household. Note that it is necessary to explicitly tell R to ignore missing values(`NA`). This is different from Stata where `1 + .= 1` (where `.` is "missing"). In R 1 + `NA` = `NA` (where `NA` means "not available"). Not adding `na.rm = TRUE` to aggregation functions such as `sum()` in Listing 5 below will not throw an error and only provide a column with `NA` for households where at least one individidual has an employed status of `NA`.

Listing 5 Employed in household

```
pp_microsim <- pp_microsim %>%
  mutate(employed = (lstatus == 1)) %>%
  group_by(hhid) %>%
  # Count within each household
  mutate(employed_hh = sum(employed, na.rm = TRUE)) %>%
  ungroup()
```

Here the original Stata code calculates income variables and aggregates them by household. We skip that because the dataset `ic` already has these elements calculated by the WB poverty team. We'll add them later as we need them.

However, as we'll see later labor income information is heavily non-reported in the dataset. Labor income is a crucial step in merging the dataset with macroeconomic information and so we will predict income for those that do not report it below. These variables are related to labor income, amount and frequency, which we have to standardized to a monthly or yearly value.

Primary and Secondary Job income:

- **emp__11** How much was %rostertitle%'s payment for wages/salary/income for last month?
- **emp__12** What period of time was the wage/income for?
- **emp__25** How much was %rostertitle%'s payment for wages/salary/income for last month?
- **emp__26** What period of time was the wage/income for?

Bonus, In-Kind, and food from job was not asked in Armenia, If it were, you should add a `mutate()` statement like the ones below for each subcategory in Listing 6. We use `coalesce(colname, 0)` when adding the `annual_labor_total` again to prevent sums of `NA`'s. This function replaces a value with 0 within the calculation if it's missing, but doesn't change its value permanently.

Now we need to check the share of individuals that are employed, but did not report income. This is done in Listing 7 below.

```
[1] "There is 28.57% of the employed population that reports no income."
```

We also need to mark income outliers as those with incomes outside 5 standard deviations.

```r
pp_microsim <- pp_microsim  %>%
  mutate(
    # Calculate standard deviation
    sd = sd(annual_labor_total, na.rm = TRUE),
    d = annual_labor_total / sd,
    # Combined outlier condition
    outlier = (d > 5) | (employed == TRUE & annual_labor_total == 0),
    # Mark potential missings
    missings = if_else(employed == TRUE, is.na(annual_labor_total), NA)
  )
```

Economic sector. The economic sectors dataset contains a lookup table for sector aggregation which we add to the `pp_microsim` database in Listing 8.

Some individuals report no sector for either their primary or secondary job. In Listing 9 we find out the sector of other family members in their home and assign the sector of whoever is closest using `fill( other_sector, .direction = "downup")`.

We then assign a specific value for missing sectors for those employed with no one else in the hh to assign value. We select services as it's the heaviest sector in the dataset (we do it like this, instead of say, any matching technique, because it's only 2 observations).

```r
pp_microsim <- pp_microsim %>%
  mutate(sector = if_else(is.na(sector) & employed == TRUE, 3, sector))
```

We provide value labels for sector factors.

```r
pp_microsim <- pp_microsim %>%
  mutate(sector_name = factor(sector, levels = c(1, 2, 3),
                              labels = c("Agriculture",
                                         "Manufacturing",
                                         "Services")))
```

We make sure that those outside the labor force (OLF) do not report a sector, which we replace with `NA` for those who meet the condition.

0.4.3 The regression

Since labor income was a key variable, which we needed to match with the future wage bill by economic activity, we first checked for missing values among employed individuals. We found that almost a third of respondents (28.6%) did not report income for either their primary or secondary job. To overcome this limitation, we used the available information from the remaining respondents to estimate an extended Mincer equation, as shown in Equation 1, and implemented in Listing 11. For the respondents with available information, we also identified outliers as those outside of five standard deviations from the mean labor income.

$$\ln(lab_i) = \beta_0 + \beta_1 \text{age}_i + \beta_2 \text{gender}_i + \beta_3 \text{educy}_i + \beta_4 \text{age}_i^2 + \beta_5 \text{marz}_i + \beta_6 \text{sector}_i + \epsilon_i \quad (1)$$

Where:

- $\ln(lab_i)$ is the natural logarithm of labor income for individual i.
- β_0 is the intercept term.
- $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ are the coefficients for the respective independent variables.
- age_i is the age of individual i.
- gender_i is a binary variable indicating the gender of individual i (1 for male, 2 for female).
- educy_i represents the level of education for individual i (ordered: 1) None to General, 2) Secondary to Vocational, 3) Higher education).
- age_i^2 is the square of the age of individual i, included to capture non-linear effects of age on labor income.
- marz_i represents the region where individual i resides.
- sector_i represents the sector of employment for individual i (i.e., agriculture, manufacturing or services).
- ϵ_i is the error term for individual i.

We first prepare our variables for the regression.

```
pp_microsim <- pp_microsim %>%
  mutate(
    educy2 = educy^2,
    age2 = age^2,
    male = case_when(
      gender == 1 ~ 1,
      gender == 2 ~ 0
    ),
    lnlab = log(annual_labor_total),
    simuli = NA_real_ # Initialize simuli
  )
```

Filter the data for regression conditions.

```
regression_data <- pp_microsim %>%
  filter(employed == TRUE & outlier == FALSE & missings == FALSE)
```

Regression model.

Predict for specific conditions

```r
pp_microsim <- pp_microsim %>%
  mutate(
    condition = (lstatus == 1 & (outlier == TRUE | missings == TRUE))
  )
```

Applying predictions.

Note: The ‘predict’ function in R does not directly support conditions within the function call, so we handle this by filtering or subsetting the data as needed.

temp2 equivalent - Note: ‘type = “response”’ might be needed depending on model type.

```r
pp_microsim$simuli[pp_microsim$condition==TRUE] <- exp(
  predict(model, pp_microsim[pp_microsim$condition==TRUE, ], type = "response"))
```

Handling negative values in ‘simuli’.

```r
pp_microsim <- pp_microsim %>%
  mutate(
    simuli = if_else(simuli < 0, 0, simuli)
  )
```

There were 8 observations that met the criteria:

We will replace `annual_labor_total` with this value for those observations.

```r
pp_microsim <- pp_microsim %>%
  mutate(annual_labor_total = if_else(
    employed == TRUE & (outlier == TRUE | missings == TRUE),
    simuli, annual_labor_total))

# And get monthly incomes for everyone
pp_microsim <- pp_microsim %>%
  mutate(monthly_labor_income = annual_labor_total / 12)
```

Merging datasets.

```
pp_microsim <- pp_microsim %>%
  left_join(consumption_aggregates, by = "hhid")
```

0.4.4 Total income and shares

Total labor income at HH level.

```
pp_microsim <- pp_microsim %>%
  group_by(hhid) %>%
  mutate(lab_hh = sum(annual_labor_total, na.rm = TRUE)) %>%
  ungroup()
```

Monthly incomes come from the `ic` data set.

```
incomes <- ic %>%
  select(interview__key, inc1, inc2, inc3, inc4, inc5, inc6, inc7, inc8)
```

Total income at HH level (the commented out portion was a less efficient way of accomplishing the same result of coalescing NAs to 0 so that the sum can be performed). Note that here we need to use the magittr pipe `%>%` instead of the newer Native Pipe `%>%` , because we need to reference the correct scope with the dot `.`.

```
pp_microsim <- pp_microsim %>%
  left_join(incomes, by = c("hhid" = "interview__key")) %>%
  mutate(across(inc5:inc8, ~replace_na(., 0))) %>%
  mutate(nli_hh = 12 * rowSums(select(., inc5:inc8), na.rm = TRUE)) %>%
  mutate(income_hh = lab_hh + nli_hh)

# pp_microsim <- pp_microsim %>%
#   left_join(incomes, join_by(hhid == interview__key)) %>%
#   mutate(nli_hh = (  coalesce(inc5) +
#                      coalesce(inc6) +
#                      coalesce(inc7) +
#                      coalesce(inc8)) * 12) %>%
#   mutate(income_hh = lab_hh + nli_hh)
```

Calculating shares:

```
pp_microsim <- pp_microsim %>%
  mutate(
    s_lab = lab_hh / income_hh,
    s_nli = nli_hh / income_hh,
    lny = log(income_hh),
    lnc = log(yhh), # comes from consumption aggregates
    mpc = yhh / income_hh
  )
```

Shares of labor and non-labor income, and additional calculations.

```
pp_microsim <- pp_microsim %>%
  mutate(
    share = if_else(employed == TRUE, annual_labor_total / lab_hh, NA_real_),
    ylb = yhh * s_lab,
    ynl = yhh * (1 - s_lab),
    ylbi = if_else(employed == TRUE, ylb * share, NA_real_)
  )
```

Final subset of data.

```
pp_microsim <- pp_microsim %>%
  select(hhid, pid, industry, yhh, ylb, ynl, ylbi, salaried,
         rural, hhsize,hhsize_R, marz.x, aepc, yhh, wgt_adj, weight,
         Foodpovln2022, Lpovln2022, Upovln2022, Avpovln2022,
         poor_Foodpovln2022, poor_Lpovln2022, poor_Upovln2022,
         poor_Avpovln2022, decile, zone, urb_rur,
         gender, age, head, rel, zone, educy, calif, sector, sector_name,
         annual_labor_total,annual_labor_income_primary,
         annual_labor_income_secondary,monthly_labor_income,
         lstatus, sector_w, NAM_1 ) %>%
  rename(marz = marz.x)

# Exporting to Stata (might be necessary for reweigthing with wentropy)
# write_dta(pp_microsim, path = "outputs/pp_microsim.dta", version = 10)
```

0.5 UN Population Projections

Now we are ready to move to our demographic projections and macroeconomic model information.

First, filtering based on country (our `iso` variable).

```r
population_projections <- population_projections  %>%
  filter(country == iso)
```

Collapsing data by summing up variables starting with "yf" and "ym" and reshaping data to long format.

```r
population_projections <- population_projections %>%
  group_by(Variant, country, cohort) %>%
  summarize(across(starts_with(c("yf", "ym")), sum)) %>%
  ungroup()
```

```
`summarise()` has grouped output by 'Variant', 'country'. You can override
using the `.groups` argument.
```

```r
population_projections <- pivot_longer(population_projections,
                                       cols = starts_with(c("yf", "ym")),
                                       names_to = c(".value", "year"),
                                       names_pattern = "(yf|ym)(.*)")
```

Creating new variable `total_population` as the sum of `yf` and `ym`. Dropping `country` variables.

```r
population_projections <- population_projections %>%
  mutate(total_population = yf + ym) %>%
  select( -country) %>%
  mutate(year = as.numeric(year))
```

Summarizing the year to find the range.

```r
minyear <- surveyyear # Make sure `surveyyear` is correctly defined
maxyear <- max(as.numeric(population_projections$year))

# Print the year range as a check
print(paste("Min Year:", minyear, "- Max Year:", maxyear))
```

```
[1] "Min Year: 2022 - Max Year: 2100"
```

```r
# With minyear and maxyear defined above
# Initialize a list to store growth data
pop_growth <- list()

# Loop over variants
variants <- unique(population_projections$Variant)
for (variant in variants) {
  for (t in minyear:maxyear) {

    # Calculate population for year t
    pop_t <- population_projections %>%
      filter(year == t, Variant == variant) %>%
      summarize(sum_pop = sum(total_population)) %>%
      pull(sum_pop)

    # Calculate population for base year
    pop_base <- population_projections %>%
      filter(year == minyear, Variant == variant) %>%
      summarize(sum_pop = sum(total_population)) %>%
      pull(sum_pop)

    # Calculate growth rate and store in list with dynamic naming
    growth_rate <- pop_t / pop_base
    pop_growth[[paste0(t, "_", variant)]] <- list(
      growth_rate = growth_rate, pop_t = pop_t
      )
  }
}

# Convert list to dataframe
pop_growth <- do.call(rbind, lapply(names(pop_growth), function(x) {
  # Extract year and variant from the name
  parts <- unlist(strsplit(x, "_"))
  year <- as.integer(parts[1])
  variant <- parts[2]

  # Create a tibble for each entry
  tibble(year = year,
         variant = variant,
         total_population = pop_growth[[x]]$pop_t,
         pop_growth_rate = pop_growth[[x]]$growth_rate)
}))
```

```r
# Arrange the dataframe for better readability
pop_growth <- arrange(pop_growth, variant, year)

# Display the first few rows of the dataframe
pop_growth[c(1:09),]
```

```
# A tibble: 9 x 4
   year variant            total_population pop_growth_rate
  <int> <chr>                         <dbl>           <dbl>
1  2022 Constant-fertility            2780.           1
2  2023 Constant-fertility            2778.           0.999
3  2024 Constant-fertility            2778.           0.999
4  2025 Constant-fertility            2776.           0.998
5  2026 Constant-fertility            2774.           0.998
6  2027 Constant-fertility            2770.           0.996
7  2028 Constant-fertility            2766.           0.995
8  2029 Constant-fertility            2761.           0.993
9  2030 Constant-fertility            2755.           0.991
```

We load elasticities.

```r
elasticities <- c(0.82, 0.9, 0.79) # Agr, Manuf, Services
yearsto <- c(2030)
```

0.6 Macro Scenarios

The following code accomplishes the following:

- Import data from Excel sheets corresponding to each scenario and combine them into one data frame.
- Rename columns, create a 'scenid' to identify scenarios, and merge with population projections.
- Calculate real wages and consumption per capita.

```r
# Macro Scenario File imported in "Datasets" section (scenario_file)
sheets <- excel_sheets(scenario_file)
scenario_sheets <- sheets[c(1,2,3)]

# Define the names of the scenarios and the variants
# modify list with the tab numbers in the Excel file
```

```r
scenarios <- scenario_sheets %>%
  # Convert all text to lowercase
  str_to_lower() %>%
  # Replace all spaces and hyphens with underscores
  str_replace_all("[ -]", "_") %>%
  # Remove the word 'scenario' or 'scenarios'
  str_remove_all("scenario?s?") %>%
  # Remove leading and trailing underscores
  str_replace_all("^_+|_+$", "")

# Create an empty list to store data frames for each scenario
scen_data_list <- list()

# Import data for each scenario and store it in the list
for (i in seq_along(scenarios)) {
  sheet_data <- read_excel(scenario_file,
                           sheet = scenario_sheets[i],
                           range = "B3:AT31",
                           col_names = FALSE)
  sheet_data$scenario_id <- scenarios[i]
  colnames(sheet_data) <- scenario_varlist$var_short_name
  scen_data_list[[i]] <- sheet_data
}
```

```
New names:
New names:
New names:
* `` -> `...1`
* `` -> `...2`
* `` -> `...3`
* `` -> `...4`
* `` -> `...5`
* `` -> `...6`
* `` -> `...7`
* `` -> `...8`
* `` -> `...9`
* `` -> `...10`
* `` -> `...11`
* `` -> `...12`
* `` -> `...13`
* `` -> `...14`
* `` -> `...15`
* `` -> `...16`
* `` -> `...17`
* `` -> `...18`
* `` -> `...19`
* `` -> `...20`
* `` -> `...21`
* `` -> `...22`
* `` -> `...23`
* `` -> `...24`
* `` -> `...25`
* `` -> `...26`
* `` -> `...27`
* `` -> `...28`
* `` -> `...29`
* `` -> `...30`
* `` -> `...31`
* `` -> `...32`
* `` -> `...33`
* `` -> `...34`
* `` -> `...35`
* `` -> `...36`
* `` -> `...37`
* `` -> `...38`
* `` -> `...39`
* `` -> `...40`
* `` -> `...41`
* `` -> `...42`
* `` -> `...43`
* `` -> `...44`
* `` -> `...45`
```

```r
# Combine all data frames into one
combined_data <- bind_rows(scen_data_list)

# Rename population_m from the data set because we will use
# UN pop projections from the other data set.
combined_data <- combined_data %>%
  rename(population_m_macrodata = population_m)

# Calculate real wages
combined_data <- combined_data %>%
  mutate(rwage_agr_m_amd = wage_agr_m_amd / cpi,
         rwage_man_m_amd = wage_man_m_amd / cpi,
         rwage_ser_m_amd = wage_ser_m_amd / cpi)

pop_data <- population_projections %>%
  group_by(Variant, year) %>%
  summarize(female = sum(yf),
            male = sum(ym),
            total_population = sum(total_population) ) %>%
  ungroup()
```

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

```r
# Filter population data to macro model years
pop_data <- pop_data %>%
  filter(year <= max(combined_data$year),
         Variant == variants[7])
# Merge the combined data with population projections
macro_data <- combined_data %>%
  left_join(pop_data, by = c("year"))

# Calculate consumption per capita and other totals
macro_data <- macro_data %>%
  mutate(
    consumption_pc = consumption_b_amd / (total_population),
    total_employment = lab_agr_1000p + lab_man_1000p + lab_ser_1000p,
    employment_rate = working_age_pop_m / total_population
    )

# Function to add growth rate columns directly in the dataframe
calculate_growth <- function(data, value_column) {
  growth_col_name <- paste0(value_column, "_growth") # dynamic name for growth column
  data %>%
    arrange(year) %>%
    group_by(Variant, scenario_id) %>%
    mutate(
      base_value = first(!!sym(value_column)),
      !!sym(growth_col_name) := !!sym(value_column) / base_value
    ) %>%
    select(-base_value) %>% # optionally remove base_value column if not needed
    ungroup()
}

# Columns to calculate growth for
value_columns <- c(
  "gdp_b_amd",           # GDP
  "consumption_b_amd",   # Consumption
  "consumption_pc",      # Consumption PC
  "remittances_b_amd",   # Remittances
  "total_employment",    # Employment
  "employment_rate",     # Employment rate
  "working_age_pop_m",   # Working age population
  "va_agr_b_amd",        # Value added agriculture
  "va_man_b_amd",        # Value added manufacturing
  "va_ser_b_amd",        # Value added services
  "wage_agr_m_amd",      # Nominal wage agriculture
  "wage_man_m_amd",      # Nominal wage manufacturing
  "wage_ser_m_amd",      # Nominal wage services
  "rwage_agr_m_amd",     # Real wage agriculture
  "rwage_man_m_amd",     # Real wage manufacturing
  "rwage_ser_m_amd"      # Real wage services
  )

# Applying the growth calculation to the macro_data for each column
for (col in value_columns) {
  macro_data <- calculate_growth(macro_data, col)
}

# Now `macro_data` will have growth rate columns for each of the variables listed
# We rearrange the dataset for clarity
macro_data <- macro_data %>%
  relocate(scenario_id, Variant, .before = year) %>%
  arrange(scenario_id, Variant, year)

# write.table(macro_data, "clipboard", sep="\t", row.names=FALSE)
```

0.7 Reweighting of the dataset

0.7.1 Aggregation of population data

This is based on a custom command to reweight the survey according to macroeconomic data for every possible combination of variant, year, and country. In the macro data we know they only used the “medium” variant and we only need to reweight for a specific year (2030) for Armenia (ARM), so we will conduct the reweighting directly with these parameters.

```r
# We join several cohorts from 0 to 29 years old and from
# 60 onwards, because the reweighting procedure works
# best if each category is at least 5% of the population
# The solution here works best for Armenia.

population_projections <- population_projections %>%
  # filter(Variant == "Medium") %>%
  # Recoding cohorts into ordered factors
    mutate(cohort_short = factor(case_when(
    cohort %in% c("P0004", "P0509","P1014",
                  "P1519","P2024", "P2529") ~ "P0029",
    cohort %in% c("P3034", "P3539") ~ "P3039",
    cohort %in% c("P4044", "P4549") ~ "P4049",
    cohort %in% c("P5054", "P5559") ~ "P5059",
    cohort %in% c("P6064", "P6569","P7074", "P7579",
                  "P8084", "P8589", "P9094", "P9599",
                  "P100up") ~ "P60up"
  ), levels = c("P0029", "P3039",
                "P4049", "P5059", "P60up"))) %>%

  # Convert factor 'cohort' to numeric codes
  mutate(cohort_code = as.integer(cohort_short))

# Checking the resulting dataset
print(pop_data)
```

```
# A tibble: 60 x 5
   Variant  year female  male total_population
   <chr>   <dbl>  <dbl> <dbl>            <dbl>
 1 Medium   1991  1867. 1750.            3618.
 2 Medium   1992  1850. 1724.            3575.
 3 Medium   1993  1799. 1658.            3457.
 4 Medium   1994  1763. 1610.            3374.
 5 Medium   1995  1741. 1581.            3323.
 6 Medium   1996  1731. 1568.            3299.
 7 Medium   1997  1719. 1552.            3271.
 8 Medium   1998  1705. 1535.            3241.
 9 Medium   1999  1689. 1517.            3206.
10 Medium   2000  1672. 1496.            3169.
```

```
# i 50 more rows
```

Let's now create cohorts in our `pp_microsim` data to match our population projection data.

```
# Convert 'age' into 'cohort' factor with levels ordered as specified
pp_microsim <- pp_microsim %>%
    mutate(cohort = factor(case_when(
    age >= 0  & age <= 29 ~ "P0029",
    age >= 30 & age <= 39 ~ "P3039",
    age >= 40 & age <= 49 ~ "P4049",
    age >= 50 & age <= 59 ~ "P5059",
    age >= 60  ~ "P60up"
  ), levels = c("P0029", "P3039", "P4049", "P5059", "P60up")))

# Convert the 'cohort' and 'gender' factor to numeric codes
pp_microsim <- pp_microsim %>%
  mutate(cohort_code = as.integer(cohort)) %>%
  mutate(gender_code = as.integer(gender))
```

We also need demographic targets for 2030

```
# Ensure pop_targets_2030 is correctly prepared
# We use the "Medium" variant = variants[7]
pop_targets_2030 <- population_projections  %>%
  filter(year == 2030, Variant == variants[7])  %>%
  group_by(cohort_code, cohort_short) %>%
    summarize(female = sum(yf),
              male   = sum(ym),
              total = sum(total_population),
              ) %>%
  ungroup()
```

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

```
pop_total <- sum(pop_targets_2030$total)

pop_targets_2030 <- pop_targets_2030 %>%
  mutate(pct_total = total / pop_total)

#writeClipboard(pop_targets_2030)
# write.table(pop_targets_2030, "clipboard", sep="\t", row.names=FALSE)
```

And economic targets from our macroeconomic scenario data. We deal with this later. Should come back to fix this so we can automate.

```
# economic_targets_2030 <- macro_data %>%
#   filter(year == 2030, Variant == "Medium", scenario_id == "baseline") %>%
#   summarize(
#     target_lab_agr = sum(lab_agr_1000p * 1000),
#     target_lab_man = sum(lab_man_1000p * 1000),
#     target_lab_ser = sum(lab_ser_1000p * 1000)
#   )
```

For a better representation of the labor market, we will take into account the combination between labor status and economic sector of the employed and adjust that combination according to the macrodata so that we can accurately model changes in total employment, sector distribution of the employed and overall population changes.

```
pp_microsim <- pp_microsim %>%
  mutate(lmarket = case_when(
    lstatus == 1 & sector_w   == 1  ~ 1,    # Agriculture
    lstatus == 1 & sector_w   == 2  ~ 2,    # Manufactures
    lstatus == 1 & sector_w   == 3  ~ 3,    # Services
    lstatus == 2 & is.na(sector_w) ~ 4,    # Unemployed
    lstatus == 3 & is.na(sector_w) ~ 4,    # Unemployed
    lstatus == 4 & is.na(sector_w) ~ 5,    # OLF

  ))
```

Note that the differences between the totals of the survey and the macro file for the base year are very much different. We'll adjust the survey only with relative growth instead of total numbers so that labor income doesn't change completely.

0.7.2 Reweigting

We use anesrake to calculate targets from known future proportions of sex, age, economic sector. We first create a target list.

```
# Target for each variable

gender_code <- c(
  sum(pop_targets_2030$male)   /
    (sum(pop_targets_2030$male)+ sum(pop_targets_2030$female)),
  sum(pop_targets_2030$female) /
    (sum(pop_targets_2030$male)+ sum(pop_targets_2030$female)))

cohort_code <- pop_targets_2030$pct_total

# Four digits are better than two in this case, raking is quite accurate.
lmarket_baseline <- c(0.1342, 0.0494, 0.2611, 0.2473, 0.3080)
lmarket_dry_hot  <- c(0.1369, 0.0489, 0.2593, 0.2473, 0.3076)
lmarket_nzs      <- c(0.1251, 0.0516, 0.2623, 0.2516, 0.3094)
# Note how similar the scenarios are

# Target list baseline
targets_baseline <- list(gender_code
                , cohort_code
                , lmarket_baseline
                )

names(targets_baseline) <- c("gender_code",
                    "cohort_code",
                    "lmarket"
                    )

# Target list Dry/Hot
targets_dry_hot <- list(gender_code
                , cohort_code
                , lmarket_dry_hot
                )

names(targets_dry_hot) <- c("gender_code",
                    "cohort_code",
                    "lmarket"
                    )

# Target list NZS
targets_nzs <- list(gender_code
                , cohort_code
                , lmarket_nzs
                )

names(targets_nzs) <- c("gender_code",
                    "cohort_code",
                    "lmarket"
                    )
```

And now we perform the reweighting, using the original weights. Initially we had used the default option type = "pctlim" combined with pctlim=0.05, because the method recommends that if reweighting changes for one variable according to its target are not of at least 5%, then it's not worth burdening the procedure with it. It then ignored sex as a reweighting variable, leaving a small percentage difference between the target and the final population. However, we then tried removing this limitation and the procedure reached convergence in 33 iterations very efficiently.

```
# Since this uses base R, we need to turn the data frame into base R object
rakedata <- as.data.frame(pp_microsim)

anesrake::anesrakefinder(targets_baseline, rakedata, choosemethod = "total")
```

```
gender_code cohort_code     lmarket
 0.03626510  0.09677000  0.07172418
```

```
outsave <- anesrake::anesrake(targets_baseline,
                    rakedata,
                    caseid = rakedata$pid,
                    #verbose = FALSE,
                    choosemethod = "total",
                    #type = "pctlim",
                    type = "nolim",
                    #cap = 100,
                    #pctlim = 0.05,
                    nlim = 3,
                    iterate = TRUE,
                    force1 = TRUE,
                    verbose = TRUE,
                    weightvec = rakedata$weight)
```

```
[1] "Raking...Iteration 1"
[1] "Current iteration changed total weights by 2361.17708851471"
[1] "Raking...Iteration 2"
[1] "Current iteration changed total weights by 343.154685460483"
[1] "Raking...Iteration 3"
[1] "Current iteration changed total weights by 50.282147123565"
[1] "Raking...Iteration 4"
```

```
[1] "Current iteration changed total weights by 15.5324150051193"
[1] "Raking...Iteration 5"
[1] "Current iteration changed total weights by 4.9125427648284"
[1] "Raking...Iteration 6"
[1] "Current iteration changed total weights by 1.55433042098091"
[1] "Raking...Iteration 7"
[1] "Current iteration changed total weights by 0.491570475878754"
[1] "Raking...Iteration 8"
[1] "Current iteration changed total weights by 0.15548860353216"
[1] "Raking...Iteration 9"
[1] "Current iteration changed total weights by 0.0491861537407502"
[1] "Raking...Iteration 10"
[1] "Current iteration changed total weights by 0.0155594639669022"
[1] "Raking...Iteration 11"
[1] "Current iteration changed total weights by 0.00492206801523239"
[1] "Raking...Iteration 12"
[1] "Current iteration changed total weights by 0.0015570434063234"
[1] "Raking...Iteration 13"
[1] "Current iteration changed total weights by 0.000492553986909977"
[1] "Raking...Iteration 14"
[1] "Current iteration changed total weights by 0.00015581417334512"
[1] "Raking...Iteration 15"
[1] "Current iteration changed total weights by 4.92901435997922e-05"
[1] "Raking...Iteration 16"
[1] "Current iteration changed total weights by 1.55924099685123e-05"
[1] "Raking...Iteration 17"
[1] "Current iteration changed total weights by 4.9324913638793e-06"
[1] "Raking...Iteration 18"
[1] "Current iteration changed total weights by 1.56034048766351e-06"
[1] "Raking...Iteration 19"
[1] "Current iteration changed total weights by 4.93596604533852e-07"
[1] "Raking...Iteration 20"
[1] "Current iteration changed total weights by 1.56144157131832e-07"
[1] "Raking...Iteration 21"
[1] "Current iteration changed total weights by 4.93947955038099e-08"
[1] "Raking...Iteration 22"
[1] "Current iteration changed total weights by 1.56252071836782e-08"
[1] "Raking...Iteration 23"
[1] "Current iteration changed total weights by 4.94344779000677e-09"
[1] "Raking...Iteration 24"
[1] "Current iteration changed total weights by 1.56241772297783e-09"
[1] "Raking...Iteration 25"
[1] "Current iteration changed total weights by 4.95822036206128e-10"
```

```
[1] "Raking...Iteration 26"
[1] "Current iteration changed total weights by 1.56211973911802e-10"
[1] "Raking...Iteration 27"
[1] "Current iteration changed total weights by 5.09479958221704e-11"
[1] "Raking...Iteration 28"
[1] "Current iteration changed total weights by 1.42659634105868e-11"
[1] "Raking...Iteration 29"
[1] "Current iteration changed total weights by 6.37030705963326e-12"
[1] "Raking...Iteration 30"
[1] "Current iteration changed total weights by 2.28768393117917e-12"
[1] "Raking...Iteration 31"
[1] "Current iteration changed total weights by 2.2706836411146e-12"
[1] "Raking converged in 31 iterations"
```

```
summary(outsave)
```

```
$convergence
[1] "Complete convergence was achieved after 31 iterations"

$base.weights
[1] "Using Base Weights Provided"

$raking.variables
[1] "gender_code" "cohort_code" "lmarket"

$weight.summary
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
 0.1034  0.6700  0.9288  1.0000  1.2682  3.3858 

$selection.method
[1] "variable selection conducted using _nolim_ - discrepancies selected using _total_."

$general.design.effect
[1] 1.244831

$gender_code
         Target Old Weights N Old Weights % Wtd N Wtd % Change in %
<NA>  0.4514133            NA            NA    NA    NA          NA
<NA>  0.5485867            NA            NA    NA    NA          NA
Total 1.0000000             0             0     0     0           0
      Resid. Disc. Orig. Disc.
<NA>            NA          NA
```

```
<NA>             NA           NA
Total             0            0

$cohort_code
         Target Old Weights N Old Weights % Wtd N Wtd % Change in %
<NA>  0.3638899            NA            NA    NA    NA          NA
<NA>  0.1420277            NA            NA    NA    NA          NA
<NA>  0.1630905            NA            NA    NA    NA          NA
<NA>  0.1042513            NA            NA    NA    NA          NA
<NA>  0.2267405            NA            NA    NA    NA          NA
Total 1.0000000             0             0     0     0           0
      Resid. Disc. Orig. Disc.
<NA>            NA          NA
<NA>            NA          NA
<NA>            NA          NA
<NA>            NA          NA
<NA>            NA          NA
Total            0           0

$lmarket
      Target Old Weights N Old Weights % Wtd N Wtd % Change in % Resid. Disc.
<NA>  0.1342            NA            NA    NA    NA          NA           NA
<NA>  0.0494            NA            NA    NA    NA          NA           NA
<NA>  0.2611            NA            NA    NA    NA          NA           NA
<NA>  0.2473            NA            NA    NA    NA          NA           NA
<NA>  0.3080            NA            NA    NA    NA          NA           NA
Total 1.0000             0             0     0     0           0            0
      Orig. Disc.
<NA>           NA
<NA>           NA
<NA>           NA
<NA>           NA
<NA>           NA
Total           0
```

```
# add weights to the dataset

rakedata$weight_2030_baseline  <- unlist(outsave[1])
n  <- length(rakedata$sector)

# Calculate the sum of original weights
original_weight_sum <- sum(rakedata$weight)
```

```r
# # Target scaling for original weights

original_weight_scaling_factor <-
  pop_data$total_population[pop_data$year == 2030] /
  pop_data$total_population[pop_data$year == 2022]

# Scaled original weights
original_weight_sum <- (original_weight_sum
                        * original_weight_scaling_factor)

# Calculate the sum of the new weights
new_weight_sum <- sum(rakedata$weight_2030_baseline)

# Scale the new weights to match the sum of the original weights
scaling_factor <- original_weight_sum / new_weight_sum
rakedata$weight_2030_baseline <- rakedata$weight_2030_baseline * scaling_factor

# Verify the adjustment
head(rakedata[, c("weight", "weight_2030_baseline")])
```

```
    weight weight_2030_baseline
1 185.7685             175.0700
2 185.7685             188.2168
3 122.7176             101.5832
4 185.7685             191.8185
5 326.8796             264.5755
6 326.8796             337.5253
```

```r
summary(rakedata$weight_2030_baseline)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  15.87  102.86  142.59  153.52  194.69  519.78 
```

```r
summary(rakedata$weight)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  21.48  109.82  156.33  154.68  192.16  326.88 
```

```r
hh_size <- rakedata %>%
  select(hhid, hhsize) %>%
  mutate(ones = 1,
         hhsize_old = hhsize) %>%
  group_by(hhid) %>%
  summarize(hhsize = sum(ones, na.rm = TRUE)) %>%
  ungroup()

rakedata <- rakedata %>%
  rename(hhsize_old = hhsize) %>%
  left_join(hh_size, join_by(hhid)) %>%
  relocate(weight, .before = weight_2030_baseline) %>%
  mutate(hh_weight_2030_baseline = weight_2030_baseline / hhsize)

pp_microsim <- tibble(rakedata)
rm(rakedata)
```

We now do the Dry/Hot Scenario. The efficient way of doing this is through a loop or sapply, but as we're strapped for time we will just repeat the code. (Needs rework.)

```r
# Since this uses base R, we need to turn the data frame into base R object
rakedata <- as.data.frame(pp_microsim)

anesrake::anesrakefinder(targets_dry_hot, rakedata, choosemethod = "total")
```

```
gender_code cohort_code     lmarket
 0.03626510  0.09677000  0.06632418
```

```r
outsave <- anesrake::anesrake(targets_dry_hot,
                    rakedata,
                    caseid = rakedata$pid,
                    #verbose = FALSE,
                    choosemethod = "total",
                    #type = "pctlim",
                    type = "nolim",
                    #cap = 100,
                    #pctlim = 0.05,
                    nlim = 3,
                    iterate = TRUE,
                    force1 = TRUE,
                    verbose = TRUE,
                    weightvec = rakedata$weight)
```

```
[1] "Raking...Iteration 1"
[1] "Current iteration changed total weights by 2346.39562345486"
[1] "Raking...Iteration 2"
[1] "Current iteration changed total weights by 325.326676946962"
[1] "Raking...Iteration 3"
[1] "Current iteration changed total weights by 47.6038687445994"
[1] "Raking...Iteration 4"
[1] "Current iteration changed total weights by 14.7805325726215"
[1] "Raking...Iteration 5"
[1] "Current iteration changed total weights by 4.67536358935004"
[1] "Raking...Iteration 6"
[1] "Current iteration changed total weights by 1.48066518168051"
[1] "Raking...Iteration 7"
[1] "Current iteration changed total weights by 0.468649510562274"
[1] "Raking...Iteration 8"
[1] "Current iteration changed total weights by 0.148353295202568"
[1] "Raking...Iteration 9"
[1] "Current iteration changed total weights by 0.046965177901018"
[1] "Raking...Iteration 10"
[1] "Current iteration changed total weights by 0.0148683286004776"
[1] "Raking...Iteration 11"
[1] "Current iteration changed total weights by 0.00470705840641751"
[1] "Raking...Iteration 12"
[1] "Current iteration changed total weights by 0.00149017464214521"
[1] "Raking...Iteration 13"
[1] "Current iteration changed total weights by 0.000471763960322724"
[1] "Raking...Iteration 14"
[1] "Current iteration changed total weights by 0.000149352453236176"
[1] "Raking...Iteration 15"
[1] "Current iteration changed total weights by 4.72824469837235e-05"
[1] "Raking...Iteration 16"
[1] "Current iteration changed total weights by 1.49688183763291e-05"
[1] "Raking...Iteration 17"
[1] "Current iteration changed total weights by 4.7388742776544e-06"
[1] "Raking...Iteration 18"
[1] "Current iteration changed total weights by 1.50024780687374e-06"
[1] "Raking...Iteration 19"
[1] "Current iteration changed total weights by 4.74952141560347e-07"
[1] "Raking...Iteration 20"
[1] "Current iteration changed total weights by 1.50361528755694e-07"
[1] "Raking...Iteration 21"
[1] "Current iteration changed total weights by 4.76025212442499e-08"
[1] "Raking...Iteration 22"
```

```
[1] "Current iteration changed total weights by 1.50707414187101e-08"
[1] "Raking...Iteration 23"
[1] "Current iteration changed total weights by 4.77042699786878e-09"
[1] "Raking...Iteration 24"
[1] "Current iteration changed total weights by 1.50992897351987e-09"
[1] "Raking...Iteration 25"
[1] "Current iteration changed total weights by 4.77459433101401e-10"
[1] "Raking...Iteration 26"
[1] "Current iteration changed total weights by 1.5339025882799e-10"
[1] "Raking...Iteration 27"
[1] "Current iteration changed total weights by 4.58121596214056e-11"
[1] "Raking...Iteration 28"
[1] "Current iteration changed total weights by 1.52340223769087e-11"
[1] "Raking...Iteration 29"
[1] "Current iteration changed total weights by 6.39277519809411e-12"
[1] "Raking...Iteration 30"
[1] "Current iteration changed total weights by 1.47665213390269e-12"
[1] "Raking...Iteration 31"
[1] "Current iteration changed total weights by 4.05270261794044e-12"
[1] "Raking converged in 31 iterations"
```

```
summary(outsave)
```

```
$convergence
[1] "Complete convergence was achieved after 31 iterations"

$base.weights
[1] "Using Base Weights Provided"

$raking.variables
[1] "gender_code" "cohort_code" "lmarket"

$weight.summary
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
 0.1032  0.6669  0.9316  1.0000  1.2685  3.3775 

$selection.method
[1] "variable selection conducted using _nolim_ - discrepancies selected using _total_."

$general.design.effect
[1] 1.243531
```

```
$gender_code
         Target Old Weights N Old Weights % Wtd N Wtd % Change in %
<NA>  0.4514133            NA            NA    NA    NA          NA
<NA>  0.5485867            NA            NA    NA    NA          NA
Total 1.0000000             0             0     0     0           0
      Resid. Disc. Orig. Disc.
<NA>            NA          NA
<NA>            NA          NA
Total            0           0

$cohort_code
         Target Old Weights N Old Weights % Wtd N Wtd % Change in %
<NA>  0.3638899            NA            NA    NA    NA          NA
<NA>  0.1420277            NA            NA    NA    NA          NA
<NA>  0.1630905            NA            NA    NA    NA          NA
<NA>  0.1042513            NA            NA    NA    NA          NA
<NA>  0.2267405            NA            NA    NA    NA          NA
Total 1.0000000             0             0     0     0           0
      Resid. Disc. Orig. Disc.
<NA>            NA          NA
<NA>            NA          NA
<NA>            NA          NA
<NA>            NA          NA
<NA>            NA          NA
Total            0           0

$lmarket
      Target Old Weights N Old Weights % Wtd N Wtd % Change in % Resid. Disc.
<NA>  0.1369            NA            NA    NA    NA          NA           NA
<NA>  0.0489            NA            NA    NA    NA          NA           NA
<NA>  0.2593            NA            NA    NA    NA          NA           NA
<NA>  0.2473            NA            NA    NA    NA          NA           NA
<NA>  0.3076            NA            NA    NA    NA          NA           NA
Total 1.0000             0             0     0     0           0            0
      Orig. Disc.
<NA>           NA
<NA>           NA
<NA>           NA
<NA>           NA
<NA>           NA
Total           0
```

```
# add weights to the dataset

rakedata$weight_2030_dry_hot  <- unlist(outsave[1])

# Calculate the sum of original weights
original_weight_sum <- sum(rakedata$weight)

# Target scaling for original weights

original_weight_scaling_factor <-
  pop_data$total_population[pop_data$year == 2030] /
  pop_data$total_population[pop_data$year == 2022]

# Scaled original weights
original_weight_sum <- (original_weight_sum
                        * original_weight_scaling_factor)

# Calculate the sum of the new weights
new_weight_sum <- sum(rakedata$weight_2030_dry_hot)

# Scale the new weights to match the sum of the original weights
scaling_factor <- original_weight_sum / new_weight_sum
rakedata$weight_2030_dry_hot <- rakedata$weight_2030_dry_hot * scaling_factor

# Verify the adjustment
head(rakedata[, c("weight", "weight_2030_dry_hot")])
```

```
    weight weight_2030_dry_hot
1 185.7685            174.1517
2 185.7685            188.2564
3 122.7176            101.8126
4 185.7685            190.5865
5 326.8796            263.8479
6 326.8796            335.3575
```

```
summary(rakedata$weight_2030_dry_hot)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  15.84  102.38  143.01  153.52  194.73  518.52
```

```r
summary(rakedata$weight)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  21.48  109.82  156.33  154.68  192.16  326.88 
```

```r
rakedata <- rakedata %>%
  mutate(hh_weight_2030_dry_hot = weight_2030_dry_hot / hhsize)

pp_microsim <- tibble(rakedata)
rm(rakedata)
```

Let’s add the NZS scenario

```r
# Since this uses base R, we need to turn the data frame into base R object
rakedata <- as.data.frame(pp_microsim)

anesrake::anesrakefinder(targets_nzs, rakedata, choosemethod = "total")
```

```
gender_code cohort_code     lmarket 
 0.03626510  0.09677000  0.08132418 
```

```r
outsave <- anesrake::anesrake(targets_nzs,
                    rakedata,
                    caseid = rakedata$pid,
                    #verbose = FALSE,
                    choosemethod = "total",
                    #type = "pctlim",
                    type = "nolim",
                    #cap = 100,
                    #pctlim = 0.05,
                    nlim = 3,
                    iterate = TRUE,
                    force1 = TRUE,
                    verbose = TRUE,
                    weightvec = rakedata$weight)
```

```
[1] "Raking...Iteration 1"
[1] "Current iteration changed total weights by 2405.38337714935"
[1] "Raking...Iteration 2"
```

```
[1] "Current iteration changed total weights by 381.11433942213"
[1] "Raking...Iteration 3"
[1] "Current iteration changed total weights by 66.9715000528318"
[1] "Raking...Iteration 4"
[1] "Current iteration changed total weights by 20.6776651602141"
[1] "Raking...Iteration 5"
[1] "Current iteration changed total weights by 6.53725119305366"
[1] "Raking...Iteration 6"
[1] "Current iteration changed total weights by 2.0599945856778"
[1] "Raking...Iteration 7"
[1] "Current iteration changed total weights by 0.649111380457645"
[1] "Raking...Iteration 8"
[1] "Current iteration changed total weights by 0.204577406691525"
[1] "Raking...Iteration 9"
[1] "Current iteration changed total weights by 0.0644801211551565"
[1] "Raking...Iteration 10"
[1] "Current iteration changed total weights by 0.0203235937837268"
[1] "Raking...Iteration 11"
[1] "Current iteration changed total weights by 0.00640584165249312"
[1] "Raking...Iteration 12"
[1] "Current iteration changed total weights by 0.00201907300818058"
[1] "Raking...Iteration 13"
[1] "Current iteration changed total weights by 0.000636396628444766"
[1] "Raking...Iteration 14"
[1] "Current iteration changed total weights by 0.000200587436619007"
[1] "Raking...Iteration 15"
[1] "Current iteration changed total weights by 6.3223652922148e-05"
[1] "Raking...Iteration 16"
[1] "Current iteration changed total weights by 1.99276214380567e-05"
[1] "Raking...Iteration 17"
[1] "Current iteration changed total weights by 6.28103589818407e-06"
[1] "Raking...Iteration 18"
[1] "Current iteration changed total weights by 1.97973583832001e-06"
[1] "Raking...Iteration 19"
[1] "Current iteration changed total weights by 6.23997950852107e-07"
[1] "Raking...Iteration 20"
[1] "Current iteration changed total weights by 1.96680178823905e-07"
[1] "Raking...Iteration 21"
[1] "Current iteration changed total weights by 6.19911701138509e-08"
[1] "Raking...Iteration 22"
[1] "Current iteration changed total weights by 1.95397621555182e-08"
[1] "Raking...Iteration 23"
[1] "Current iteration changed total weights by 6.15833799233467e-09"
```

```
[1] "Raking...Iteration 24"
[1] "Current iteration changed total weights by 1.94083731031025e-09"
[1] "Raking...Iteration 25"
[1] "Current iteration changed total weights by 6.12484576945072e-10"
[1] "Raking...Iteration 26"
[1] "Current iteration changed total weights by 1.92554375222365e-10"
[1] "Raking...Iteration 27"
[1] "Current iteration changed total weights by 5.94729127056937e-11"
[1] "Raking...Iteration 28"
[1] "Current iteration changed total weights by 1.94124161190246e-11"
[1] "Raking...Iteration 29"
[1] "Current iteration changed total weights by 6.34514663033769e-12"
[1] "Raking...Iteration 30"
[1] "Current iteration changed total weights by 3.0190572264388e-12"
[1] "Raking...Iteration 31"
[1] "Current iteration changed total weights by 2.23793206188816e-12"
[1] "Raking...Iteration 32"
[1] "Current iteration changed total weights by 0"
[1] "Raking...Iteration 33"
[1] "Current iteration changed total weights by 0"
[1] "Raking converged in 33 iterations"
```

```r
summary(outsave)
```

```
$convergence
[1] "Complete convergence was achieved after 33 iterations"

$base.weights
[1] "Using Base Weights Provided"

$raking.variables
[1] "gender_code" "cohort_code" "lmarket"

$weight.summary
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
 0.1064  0.6667  0.9342  1.0000  1.2586  3.4331 

$selection.method
[1] "variable selection conducted using _nolim_ - discrepancies selected using _total_."

$general.design.effect
[1] 1.24885
```

```
$gender_code
         Target Old Weights N Old Weights % Wtd N Wtd % Change in %
<NA>  0.4514133            NA            NA    NA    NA          NA
<NA>  0.5485867            NA            NA    NA    NA          NA
Total 1.0000000             0             0     0     0           0
      Resid. Disc. Orig. Disc.
<NA>            NA          NA
<NA>            NA          NA
Total            0           0

$cohort_code
         Target Old Weights N Old Weights % Wtd N Wtd % Change in %
<NA>  0.3638899            NA            NA    NA    NA          NA
<NA>  0.1420277            NA            NA    NA    NA          NA
<NA>  0.1630905            NA            NA    NA    NA          NA
<NA>  0.1042513            NA            NA    NA    NA          NA
<NA>  0.2267405            NA            NA    NA    NA          NA
Total 1.0000000             0             0     0     0           0
      Resid. Disc. Orig. Disc.
<NA>            NA          NA
<NA>            NA          NA
<NA>            NA          NA
<NA>            NA          NA
<NA>            NA          NA
Total            0           0

$lmarket
      Target Old Weights N Old Weights % Wtd N Wtd % Change in % Resid. Disc.
<NA>  0.1251            NA            NA    NA    NA          NA           NA
<NA>  0.0516            NA            NA    NA    NA          NA           NA
<NA>  0.2623            NA            NA    NA    NA          NA           NA
<NA>  0.2516            NA            NA    NA    NA          NA           NA
<NA>  0.3094            NA            NA    NA    NA          NA           NA
Total 1.0000             0             0     0     0           0            0
      Orig. Disc.
<NA>           NA
<NA>           NA
<NA>           NA
<NA>           NA
<NA>           NA
Total           0
```

```r
# add weights to the dataset

rakedata$weight_2030_nzs  <- unlist(outsave[1])

# Calculate the sum of original weights
original_weight_sum <- sum(rakedata$weight)

# Target scaling for original weights

original_weight_scaling_factor <-
  pop_data$total_population[pop_data$year == 2030] /
  pop_data$total_population[pop_data$year == 2022]

# Scaled original weights
original_weight_sum <- (original_weight_sum
                        * original_weight_scaling_factor)

# Calculate the sum of the new weights
new_weight_sum <- sum(rakedata$weight_2030_nzs)

# Scale the new weights to match the sum of the original weights
scaling_factor <- original_weight_sum / new_weight_sum
rakedata$weight_2030_nzs <- rakedata$weight_2030_nzs * scaling_factor

# Verify the adjustment
head(rakedata[, c("weight", "weight_2030_nzs")])
```

```
    weight weight_2030_nzs
1 185.7685        175.7182
2 185.7685        188.4089
3 122.7176        103.4375
4 185.7685        192.4717
5 326.8796        272.2376
6 326.8796        338.6745
```

```r
summary(rakedata$weight_2030_nzs)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  16.33  102.36  143.42  153.52  193.22  527.05 
```

```r
summary(rakedata$weight)
```

```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  21.48  109.82  156.33  154.68  192.16  326.88 
```

```r
rakedata <- rakedata %>%
  mutate(hh_weight_2030_nzs = weight_2030_nzs / hhsize)
```

Weights for the household database

```r
# We calculate new weights for households in the hh database
weights_scenarios <- rakedata %>%
  group_by(hhid) %>%
  summarize(
    hh_weight_2030_baseline =
      sum(hh_weight_2030_baseline, na.rm = TRUE),
    hh_weight_2030_dry_hot =
      sum(hh_weight_2030_dry_hot, na.rm = TRUE),
    hh_weight_2030_nzs =
      sum(hh_weight_2030_nzs, na.rm = TRUE)
    )

# We return rakedata to data frame pp_microsim and get rid of rakedata
pp_microsim <- tibble(rakedata)
rm(rakedata)
```

0.7.3 Rescaling labor income according to changes to the wage bill

As a last step, we rescale labor income according to changes to the wage bill in the macro scenario.

```r
# Wage rescale factor by sector from macro (Agriculture, Manufacturing, Services)
wrf_2030_baseline  <- c(1.250520168, 1.336828769, 1.378384149)
wrf_2030_dry_hot   <- c(1.287103700, 1.297391076, 1.343485236)
wrf_2030_nzs       <- c(1.054278195, 1.317612666, 1.272275437)

# We check the wage bill by sector
wages_by_sector <- pp_microsim %>%
  filter(!is.na(sector_w)) %>%
  group_by(sector_w, .drop = TRUE) %>%
  summarize(
    wages_2022 = sum(annual_labor_total * weight, na.rm = TRUE),
    wages_2030_baseline =
      sum(annual_labor_total * weight_2030_baseline, na.rm = TRUE),
    wages2030_dry_hot   =
      sum(annual_labor_total * weight_2030_dry_hot, na.rm = TRUE),
    wages2030_nzs    =
      sum(annual_labor_total * weight_2030_nzs, na.rm = TRUE)
  )


# Compare how much it changed with reweighting with how it should have changed
# Derive coefficients (wtc_2030) from that
wages_by_sector <- wages_by_sector %>%
  mutate(
    wages_target_2030_baseline = case_when(
      sector_w == 1 ~ wages_2022 * wrf_2030_baseline[1],
      sector_w == 2 ~ wages_2022 * wrf_2030_baseline[2],
      sector_w == 3 ~ wages_2022 * wrf_2030_baseline[3],
      .default = NA
    ),
    wages_target2030_dry_hot = case_when(
      sector_w == 1 ~ wages_2022 * wrf_2030_dry_hot[1],
      sector_w == 2 ~ wages_2022 * wrf_2030_dry_hot[2],
      sector_w == 3 ~ wages_2022 * wrf_2030_dry_hot[3],
      .default = NA
    ),
    wages_target2030_nzs = case_when(
      sector_w == 1 ~ wages_2022 * wrf_2030_nzs[1],
      sector_w == 2 ~ wages_2022 * wrf_2030_nzs[2],
      sector_w == 3 ~ wages_2022 * wrf_2030_nzs[3],
      .default = NA
    ),
    wtc_2030_baseline = wages_target_2030_baseline / wages_2030_baseline,
    wtc_2030_dry_hot = wages_target2030_dry_hot / wages2030_dry_hot,
    wtc_2030_nzs = wages_target2030_nzs / wages2030_nzs
    )

# wages_by_sector %>%
#   gt()
# write.table(wages_by_sector, "clipboard", sep="\t", row.names=FALSE)
```

We then add the coefficient to rescale each wage by sector

```r
# Assign rescale the annual and monthly wage depending on the sector
# Quick way, but needs to be put in a sapply statement or loop
pp_microsim <- pp_microsim %>%
  rename(monthly_labor_income_2022 = monthly_labor_income,
         annual_labor_total_2022 = annual_labor_total) %>%
  mutate(
    monthly_labor_income_2030_baseline = case_when(
      sector_w == 1 ~ monthly_labor_income_2022 * wages_by_sector$wtc_2030_baseline[1],
      sector_w == 2 ~ monthly_labor_income_2022 * wages_by_sector$wtc_2030_baseline[2],
      sector_w == 3 ~ monthly_labor_income_2022 * wages_by_sector$wtc_2030_baseline[3],
      TRUE ~ NA
    ),
    annual_labor_total_2030_baseline = case_when(
      sector_w == 1 ~ annual_labor_total_2022 * wages_by_sector$wtc_2030_baseline[1],
      sector_w == 2 ~ annual_labor_total_2022 * wages_by_sector$wtc_2030_baseline[2],
      sector_w == 3 ~ annual_labor_total_2022 * wages_by_sector$wtc_2030_baseline[3],
      TRUE ~ NA
    ),
    monthly_labor_income_2030_dry_hot = case_when(
      sector_w == 1 ~ monthly_labor_income_2022 * wages_by_sector$wtc_2030_dry_hot[1],
      sector_w == 2 ~ monthly_labor_income_2022 * wages_by_sector$wtc_2030_dry_hot[2],
      sector_w == 3 ~ monthly_labor_income_2022 * wages_by_sector$wtc_2030_dry_hot[3],
      TRUE ~ NA
    ),
    annual_labor_total_2030_dry_hot = case_when(
      sector_w == 1 ~ annual_labor_total_2022 * wages_by_sector$wtc_2030_dry_hot[1],
      sector_w == 2 ~ annual_labor_total_2022 * wages_by_sector$wtc_2030_dry_hot[2],
      sector_w == 3 ~ annual_labor_total_2022 * wages_by_sector$wtc_2030_dry_hot[3],
      TRUE ~ NA
    ),
    monthly_labor_income_2030_nzs = case_when(
      sector_w == 1 ~ monthly_labor_income_2022 * wages_by_sector$wtc_2030_nzs[1],
      sector_w == 2 ~ monthly_labor_income_2022 * wages_by_sector$wtc_2030_nzs[2],
      sector_w == 3 ~ monthly_labor_income_2022 * wages_by_sector$wtc_2030_nzs[3],
      TRUE ~ NA
    ),
    annual_labor_total_2030_nzs = case_when(
      sector_w == 1 ~ annual_labor_total_2022 * wages_by_sector$wtc_2030_nzs[1],
      sector_w == 2 ~ annual_labor_total_2022 * wages_by_sector$wtc_2030_nzs[2],
      sector_w == 3 ~ annual_labor_total_2022 * wages_by_sector$wtc_2030_nzs[3],
      TRUE ~ NA
    )
    )

# This takes care of different household members coming from different sectors
hh_li <- pp_microsim %>%
  group_by(hhid) %>%
  summarize(mli_2022 = sum(monthly_labor_income_2022, na.rm = TRUE),
            mli_2030_baseline = sum(monthly_labor_income_2030_baseline, na.rm = TRUE),
            mli_2030_dry_hot = sum(monthly_labor_income_2030_dry_hot, na.rm = TRUE),
            mli_2030_nzs = sum(monthly_labor_income_2030_nzs, na.rm = TRUE),
            mli_coef_2030_baseline = if_else(mli_2022 == 0, 1, mli_2030_baseline / mli_2022)
            mli_coef_2030_dry_hot = if_else(mli_2022 == 0, 1, mli_2030_dry_hot / mli_2022),
            mli_coef_2030_nzs = if_else(mli_2022 == 0, 1, mli_2030_nzs / mli_2022)
            )%>%
  select(hhid,
         mli_2022,
         mli_2030_baseline,
         mli_2030_dry_hot,
         mli_2030_nzs,
         mli_coef_2030_baseline,
         mli_coef_2030_dry_hot,
         mli_coef_2030_nzs)

ic_microsim <- ic %>%
  left_join(hh_li, join_by(interview__key == hhid)) %>%
  left_join(weights_scenarios, join_by(interview__key == hhid)) %>%
  rename(inc2_2022 = inc2,
         inc3_2022 = inc3,
         totalinc_2022 = totalinc) %>%
  mutate(
    mli_coef_2030_baseline =
      if_else(
        is.na(mli_coef_2030_baseline), 1,mli_coef_2030_baseline),
    mli_coef_2030_dry_hot =
      if_else(
        is.na(mli_coef_2030_dry_hot), 1,mli_coef_2030_dry_hot),
    mli_coef_2030_nzs =
      if_else(
        is.na(mli_coef_2030_nzs), 1,mli_coef_2030_nzs)
    ) %>%
  mutate(
    inc2_2030_baseline = inc2_2022 * mli_coef_2030_baseline,
    inc3_2030_baseline = inc3_2022 * mli_coef_2030_baseline,
    inc2_2030_dry_hot  = inc2_2022 * mli_coef_2030_dry_hot,
    inc3_2030_dry_hot  = inc3_2022 * mli_coef_2030_dry_hot,
    inc2_2030_nzs  = inc2_2022 * mli_coef_2030_nzs,
    inc3_2030_nzs  = inc3_2022 * mli_coef_2030_nzs
    ) %>%
  mutate(
    totalinc_2030_baseline =
      totalinc_2022 - coalesce(inc2_2022,0) - coalesce(inc3_2022,0) +
      coalesce(inc2_2030_baseline,0) + coalesce(inc3_2030_baseline,0),
    totalinc_2030_dry_hot =
      totalinc_2022 - coalesce(inc2_2022,0) - coalesce(inc3_2022,0) +
      coalesce(inc2_2030_dry_hot,0) + coalesce(inc3_2030_dry_hot,0),
    totalinc_2030_nzs_noctr =
      totalinc_2022 - coalesce(inc2_2022,0) - coalesce(inc3_2022,0) +
      coalesce(inc2_2030_nzs,0) + coalesce(inc3_2030_nzs,0)
    )

# Calculate quantiles and create 'breaks'
breaks <- Hmisc::wtd.quantile(ic_microsim$totalinc_2030_nzs_noctr,
                             weights = ic_microsim$hh_weight_2030_nzs,
                             probs = seq(0.1, 0.9, 0.1))

# Assign decile groups directly without creating an intermediate income_decile column
ic_microsim <- ic_microsim %>%
  mutate(totalinc_2030_nzs_noctr =
           if_else(is.na(totalinc_2030_nzs_noctr), 0,totalinc_2030_nzs_noctr)) %>%
  mutate(income_decile_group = cut(totalinc_2030_nzs_noctr,
                                   breaks = c(-Inf, breaks, Inf),
                                   labels = 1:10,
                                   include.lowest = TRUE))

income_decile_group <- ic_microsim %>%
  select(interview__key, income_decile_group)
```

```
ic_microsim <- ic_microsim %>%
  mutate(
    totinc_coef_2030_baseline =
      if_else(
        totalinc_2022 == 0,
        1,
        totalinc_2030_baseline / totalinc_2022),
    totinc_coef_2030_dry_hot =
      if_else(
        totalinc_2022 == 0,
        1,
        totalinc_2030_dry_hot / totalinc_2022),
    totinc_coef_2030_nzs_noctr =
      if_else(
        totalinc_2022 == 0,
        1,
        totalinc_2030_nzs_noctr / totalinc_2022)
    ) %>%
  mutate(
    totinc_coef_2030_baseline =
      if_else(
        is.na(totinc_coef_2030_baseline),
        1,
        totinc_coef_2030_baseline),
    totinc_coef_2030_dry_hot =
      if_else(
        is.na(totinc_coef_2030_dry_hot),
        1,
        totinc_coef_2030_dry_hot),
    totinc_coef_2030_nzs_noctr =
      if_else(
        is.na(totinc_coef_2030_nzs_noctr),
        1,
        totinc_coef_2030_nzs_noctr)
    )


ic_coef_scenarios <- ic_microsim %>%
  select(
    interview__key,
    totinc_coef_2030_baseline,
    totinc_coef_2030_dry_hot,
    totinc_coef_2030_nzs_noctr
    )
```

We check that our reweighting was successful

```
# table <- pp_microsim %>%
#   group_by(cohort) %>%
# #  group_by(lmarket) %>%
# #  group_by(gender) %>%
#   summarize(no_weight = sum(n(), na.rm = TRUE),
#             total_pp = sum(weight, na.rm = TRUE)) %>%
#   ungroup()
#
# table %>%
#   gt() %>%
#   fmt_number(columns = total_pp, decimals = 0)
#
# write.table(
#   table,
#   "clipboard", sep="\t", row.names=FALSE
#   )
```

0.8 Microsimulation

We now implement different shocks according to various scenarios.

0.8.1 Macro scenarios without additional impacts

For the baseline we only adjust labor income according to the reweighting procedure and rescaling of the wage bill.

```
ca_microsim <- ca %>%
  left_join(weights_scenarios, join_by(hhid == hhid)) %>%
  left_join(ic_coef_scenarios, join_by(hhid == interview__key)) %>%
  # We adjust total consumption by the income coefficient
  rename(
    totc_2022 = totc,
    poor_Avpovln2022_2022 = poor_Avpovln2022
    ) %>%
  mutate(
    totc_2030_baseline   = totc_2022 * totinc_coef_2030_baseline,
    totc_2030_dry_hot    = totc_2022 * totinc_coef_2030_dry_hot,
    totc_2030_nzs_noctr  = totc_2022 * totinc_coef_2030_nzs_noctr
    )
```

Here we add back the tax revenue

Add back carbon tax revenue. We estimated weighted income deciles above and mapped number of households by decile. We divided the revenue by that number and we add that amount by the first four income deciles in this manner. Again, another one calculated in Excel because of time constraints. Needs fixing to make automatic.

```r
ca_microsim <- ca_microsim %>%
  left_join(income_decile_group, join_by(hhid == interview__key)) %>%
  mutate(
    totc_2030_nzs =
      # Urban 40% and Rural 60%
      case_when(
        # Urban
        income_decile_group == 1 & urb_rur == 1 ~
          totc_2030_nzs_noctr + (1546.29 * hhsize),
        income_decile_group == 2 & urb_rur == 1 ~
          totc_2030_nzs_noctr + (1610.65 * hhsize),
        income_decile_group == 3 & urb_rur == 1 ~
          totc_2030_nzs_noctr + (1251.14 * hhsize),
        income_decile_group == 4 & urb_rur == 1 ~
          totc_2030_nzs_noctr + (1134.21 * hhsize),
        # Rural
        income_decile_group == 1 & urb_rur == 2 ~
          totc_2030_nzs_noctr + (6323.09 * hhsize),
        income_decile_group == 2 & urb_rur == 2 ~
          totc_2030_nzs_noctr + (6109.07 * hhsize),
        income_decile_group == 3 & urb_rur == 2 ~
          totc_2030_nzs_noctr + (5599.16 * hhsize),
        income_decile_group == 4 & urb_rur == 2 ~
          totc_2030_nzs_noctr + (4420.53 * hhsize),
        .default = totc_2030_nzs_noctr
      )
  )
```

And recalculate poverty.

```r
ca_microsim <- ca_microsim %>%
  rename(
    aec_r_2022 = aec_r,
    weight_2022 = weight,
    weight_2030_baseline = hh_weight_2030_baseline,
    weight_2030_dry_hot = hh_weight_2030_dry_hot,
    weight_2030_nzs = hh_weight_2030_nzs
    ) %>%
  mutate(
    aec_r_2030_baseline =
      totc_2030_baseline / ae_r / PI,
    aec_r_2030_dry_hot =
      totc_2030_dry_hot  / ae_r / PI,
    aec_r_2030_nzs =
      totc_2030_nzs  / ae_r / PI
    ) %>%
  # Official poverty line
  mutate(
    poor_Avpovln2022_2030_baseline =
      if_else(aec_r_2030_baseline < 52883, 1, 0),
    poor_Avpovln2022_2030_dry_hot  =
      if_else(aec_r_2030_dry_hot  < 52883, 1, 0),
    poor_Avpovln2022_2030_nzs      =
      if_else(aec_r_2030_nzs      < 52883, 1, 0)
    )
```

Test

```
test_baseline <- ca_microsim %>%
  rename(
    poor_original = poor_Avpovln2022_2022,
    poor_2030_baseline = poor_Avpovln2022_2030_baseline,
    poor_2030_dry_hot = poor_Avpovln2022_2030_dry_hot,
    poor_2030_nzs = poor_Avpovln2022_2030_nzs
    ) %>%
  group_by(poor_original) %>%
  summarize(
    no_hh_2022 = sum(weight_2022, na.rm = TRUE),
    no_pp_2022 = sum(weight_2022 * hhsize, na.rm = TRUE),
    # no_hh_baseline = sum(weight_2030_baseline, na.rm = TRUE),
    # no_pp_baseline = sum(weight_2030_baseline * hhsize, na.rm = TRUE),
    # no_hh_dry_hot = sum(weight_2030_dry_hot, na.rm = TRUE),
    # no_pp_dry_hot = sum(weight_2030_dry_hot * hhsize, na.rm = TRUE),
    # no_hh_nzs = sum(weight_2030_nzs, na.rm = TRUE),
    # no_pp_nzs = sum(weight_2030_nzs * hhsize, na.rm = TRUE)
    ) %>%
  ungroup()
```

```
test_baseline %>%
  gt()
```

Poor, Avpovln2022	no_hh_2022	no_pp_2022
0	659638.8	2149568.6
1	143688.2	704957.6

```
write.table(test_baseline, "clipboard", sep="\t", row.names=FALSE)
```

Let's plot the distributions.

```
# # Basic density plot comparing equivalized consumption per capita
# ggplot(ca_microsim,
#        aes(x = aec_r_2030_nzs, fill = 'NZS')) +
#   geom_density(alpha = 0.5) +
#   # geom_density(
#   #   data = ca_microsim_cc,
#   #   aes(x = aec_r_2030_dry_hot, fill = 'Dry/Hot'),
#   #   alpha = 0.5) +
#   # geom_density(
#   #   data = ca_microsim_cc,
#   #   aes(x = aec_r_2030_dry_hot_food2, fill = 'Dry/Hot + Food Price'),
#   #   alpha = 0.5) +
#   geom_density(
#     data = ca_microsim,
#     aes(x = aec_r_2030_dry_hot, fill = 'Dry/Hot'),
#     alpha = 0.5) +
#   geom_density(
#     data = ca_microsim,
#     aes(x = aec_r_2030_baseline, fill = 'Baseline'),
#     alpha = 0.5) +
#   labs(
#     fill = "Scenario Variant",
#     # title = "Comparison of Consumption Distributions",
#     x = "Equivalized consumption (Dram)",
#     y = "Probability") +
#   theme_minimal()+
#   coord_cartesian(xlim = c(0, 500000),
#           #        ylim = c(0.000005,0.0000160)
#                   ) + # Zoom in without removing data
#   scale_x_continuous(labels = scales::comma) +
#   scale_y_continuous(labels = scales::comma)+
#   geom_vline(xintercept = 55883,
#               color = "red",
#               linetype = "dotted",
#               linewidth =0.8) +
#   annotate("text",
#           x = 55883,
#           y = 0.0000110,
#           #label = "Poverty line\nAMD 55,883",
#           label = "Poverty line",
#           color = "black",
#           hjust = -0.1,
#           # vjust = -3.5,
#           #angle = 90,
#           size = 3)
```

And we also plot the cumulative distributions.

```
# # Plot the cumulative distribution with left-facing arrows
# ggplot(ca_microsim,
#       aes(x = aec_r_2030_baseline, color = 'Direct CC + Food Price')) +
#   stat_ecdf(geom = "step") +
#   # stat_ecdf(data = ca_microsim_cc,
#   #           aes(x = aec_r_2030_baseline_lab_avg, color = 'Baseline + Labor Productivity')
#   stat_ecdf(data = ca_microsim_cc,
#             aes(x = aec_r_2030_baseline_lab_cc_avg, color = 'Direct CC')) +
#   stat_ecdf(data = ca_microsim_cc,
#             aes(x = aec_r_2030_baseline, color = 'Baseline')) +
#   labs(
#     color = "Scenario Variant",
#     # title = "Comparison of Cumulative Consumption Distributions",
#     x = "Equivalized consumption (Dram)",
#     y = "Cumulative Probability") +
#   theme_minimal() +
#   coord_cartesian(xlim = c(40000, 110000)) +
#   scale_x_continuous(labels = scales::comma) +
#   # geom_vline(xintercept = 55883,
#   #             color = "red",
#   #             linetype = "dotted",
#   #             linewidth = 0.8) +
#   # annotate("text",
#   #          x = 55883,
#   #          y = 0.5,
#   #          label = "Poverty line",
#   #          color = "black",
#   #          hjust = -0.1,
#   #          size = 3) +
#   annotate("segment", x = 70000, xend = 65000, y = 0.2, yend = 0.2,
#            arrow = arrow(length = unit(0.3, "cm")), color = "black") +
#   annotate("text", x = 72500, y = 0.2, label = "Shift due to shocks", hjust = 0)
#   # annotate("segment", x = 80000, xend = 75000, y = 0.4, yend = 0.4,
#   #          arrow = arrow(length = unit(0.3, "cm")), color = "black") +
#   # annotate("text", x = 82500, y = 0.4, label = "Shift due to shocks", hjust = 0)
```

0.8.2 Climate change

In these sections we use Administrative Level 1 data on yield losses and labor productivity losses due to climate change that are provided in the study commissioned for Armenia's CCDR *Estimating the Economic Impacts of Climate Change in Armenia* (Strzepek et al., 2024).

In the climate change scenario, we ask ourselves, what would happen if agriculture revenues from crops and livestock are reduced due to losses in productivity due to heat? For this, we use crops data.

We add a moving window average and max value for our labor productivity data.

```
# First calculate moving window average
labor_productivity <- labor_productivity %>%
  group_by(ADM1_EN,
           clim_scenario) %>%
  arrange(year) %>%
  # Moving window average 5 years before, 5 after
  mutate(
    moving_avg = rollapply(
      pct_change_productivity,
      width = 11,
      FUN = mean,
      partial = TRUE,
      align = "center",
      fill = NA,
      na.rm = TRUE
    ),
    # Moving window max value 5 years before, 5 after
    # Since it's expressed in negative values (min) is the maximum
    moving_max = rollapply(
      pct_change_productivity,
      width = 11,
      FUN = min,
      partial = TRUE,
      align = "center",
      fill = NA,
      na.rm = TRUE
    )
  ) %>%
  ungroup()

# Clim scenarios to select
cs <- unique(labor_productivity$clim_scenario)

# Moving average for year of interest
lab_loss_avg <- labor_productivity %>%
  filter(clim_scenario == cs[1], year == yearsto[1]) %>%
  select(-pct_change_productivity,
         -ADM1_PCODE,
         -year,
         -clim_scenario,
         -moving_max) %>%
  pivot_wider(names_from = sector, values_from = moving_avg) %>%
  rename(agr_avg = Agriculture,
         man_avg = Manufacturing,
         ser_avg = Services)

# Max value for year of interest
lab_loss_max <- labor_productivity %>%
  filter(clim_scenario == cs[1], year == yearsto[1]) %>%
  select(-pct_change_productivity,
         -ADM1_PCODE,
         -year,
         -clim_scenario,
         -moving_avg) %>%
  pivot_wider(names_from = sector, values_from = moving_max) %>%
  rename(agr_max = Agriculture,
         man_max = Manufacturing,
         ser_max = Services)
```

We add a moving window average and max value for our crops and livestock productivity data.

```r
# First calculate moving window average
crops_productivity <- crops_productivity %>%
  group_by(NAM_1, climate_scenario) %>%
  arrange(year) %>%
  # Moving window average
  mutate(
    moving_avg = rollapply(
      pct_change_prod,
      width = 11,
      # 5 years before, 5 after + reference year = 11
      FUN = mean,
      partial = TRUE,
      align = "center",
      fill = NA,
      na.rm = TRUE
    ),
    # Moving window max value 5 years before, 5 after
    # Since it's expressed in negative values (min) is the maximum
    moving_max = rollapply(
      pct_change_prod,
      width = 11,
      FUN = min,
      partial = TRUE,
      align = "center",
      fill = NA,
      na.rm = TRUE
    )
  ) %>%
  ungroup()

# Clim scenarios to select
cs <- unique(crops_productivity$climate_scenario)

# Moving average for year of interest
crops_pdcvty_loss <- crops_productivity %>%
  filter(climate_scenario == cs[1],
         year == yearsto[1]) %>%
  select(-pct_change_prod,
         -GID_1,
         -year,
         -climate_scenario) %>%
  rename(crops_avg_loss = moving_avg,
         crops_max_loss = moving_max)
```

And we do the same for livestock productivity.In this case, there is also disaggregation by Marz.

```
# First calculate moving window average
livestock_productivity <- livestock_productivity %>%
  group_by(NAM_1, climate.scenario) %>%
  arrange(year) %>%
  # Moving window average
  mutate(
    moving_avg = rollapply(
      pct_change_prod,
      width = 11,
      # 5 years before, 5 after + reference year = 11
      FUN = mean,
      partial = TRUE,
      align = "center",
      fill = NA,
      na.rm = TRUE
    ),
    # Moving window max value 5 years before, 5 after
    # Since it's expressed in negative values (min) is the maximum
    moving_max = rollapply(
      pct_change_prod,
      width = 11,
      FUN = min,
      partial = TRUE,
      align = "center",
      fill = NA,
      na.rm = TRUE
    )
  ) %>%
  ungroup()

# Clim scenarios to select
cs <- unique(livestock_productivity$climate.scenario)

# Moving average for year of interest
lvstk_pdcvty_loss <- livestock_productivity %>%
  filter(climate.scenario == cs[1],
         year == yearsto[1]) %>%
  select(-pct_change_prod,
         -year,
         -climate.scenario) %>%
  rename(lvstk_avg_loss = moving_avg,
         lvstk_max_loss = moving_max)
```

And then we introduce these values in our ag income and labor income data. First, we attach the percentage losses to the appropriate data set.

```
# Persons processed dataset
pp_microsim_cc <- pp_microsim %>%
  left_join(lab_loss_avg,
            join_by(NAM_1 == ADM1_EN)) %>%
  left_join(lab_loss_max,
            join_by(NAM_1 == ADM1_EN))

# Household income processed dataset
ic_microsim_cc <- ic_microsim %>%
  left_join(crops_pdcvty_loss,
            join_by(NAM_1 == NAM_1)) %>%
  left_join(lvstk_pdcvty_loss,
            join_by(NAM_1))

##write.table(lab_loss_avg, "clipboard", sep="\t", row.names=FALSE)
```

And we first shock labor income.

```
# Labor income according to sector
pp_microsim_cc <- pp_microsim_cc %>%
  mutate(sector = as.numeric(sector)) %>%
  mutate(
    mli_2030_baseline_lab_avg =
      case_when(
        sector == 1 ~
          monthly_labor_income_2030_baseline *
          (1 + agr_avg),
        sector == 2 ~
          monthly_labor_income_2030_baseline *
          (1 + man_avg),
        sector == 3 ~
          monthly_labor_income_2030_baseline *
          (1 + ser_avg),
        TRUE ~ NA
      )
  ) %>%
  mutate(
    mli_2030_baseline_lab_max =
      case_when(
        # * 1000 because its thousands of Dram
        sector == 1 ~
          monthly_labor_income_2030_baseline *
          (1 + agr_max),
        sector == 2 ~
          monthly_labor_income_2030_baseline *
          (1 + man_max),
        sector == 3 ~
          monthly_labor_income_2030_baseline *
          (1 + ser_max),
        TRUE ~ NA
      )
  )
```

We aggregate at household level and take note of the percent difference between the two labor incomes, so that we can impact labor income by that amount. We don't do it with absolute numbers because we don't know the assumptions made by the poverty team to construct the income variable.

```
ic_new_incomes <- pp_microsim_cc %>%
  group_by(hhid) %>%
  summarize(
    mli_2030_baseline_lab_avg =
      sum(mli_2030_baseline_lab_avg, na.rm = TRUE),
    mli_2030_baseline_lab_max =
      sum(mli_2030_baseline_lab_max, na.rm = TRUE),
    mli_original =
      sum(monthly_labor_income_2030_baseline, na.rm = TRUE)
  ) %>%
  mutate(
    mli_2030_baseline_lab_avg_coef =
      if_else(
        mli_original == 0 | is.na(mli_original),
        1,
        mli_2030_baseline_lab_avg / mli_original
      ),
    mli_2030_baseline_lab_max_coef =
      if_else(
        mli_original == 0 | is.na(mli_original),
        1,
        mli_2030_baseline_lab_max / mli_original
      )
  ) %>%
  ungroup()

ic_microsim_cc <- ic_microsim_cc %>%
  left_join(ic_new_incomes,
            join_by(interview__key == hhid)) %>%
  mutate(
    inc2_2030_baseline_lab_avg =
      inc2_2030_baseline * mli_2030_baseline_lab_avg_coef,
    inc2_2030_baseline_lab_max =
      inc2_2030_baseline * mli_2030_baseline_lab_max_coef,
    inc3_2030_baseline_lab_avg =
      inc3_2030_baseline * mli_2030_baseline_lab_avg_coef,
    inc3_2030_baseline_lab_max =
      inc3_2030_baseline * mli_2030_baseline_lab_max_coef
  )
```

And now we impact agricultural income `cropinc` and livestock income`lvstk`.

```
ic_microsim_cc <- ic_microsim_cc %>%
  mutate(
    cropinc_2030_baseline_cc_avg =
      cropinc * (1 + crops_avg_loss),
    cropinc_2030_baseline_cc_max =
      cropinc * (1 + crops_max_loss),
    lvstk_2030_baseline_cc_avg =
      lvstk * (1 + lvstk_avg_loss),
    lvstk_2030_baseline_cc_max =
      lvstk * (1 + lvstk_max_loss)
    )
```

And recalculate total income.

```r
ic_microsim_cc <- ic_microsim_cc %>%
  mutate(
    totalinc_2030_baseline_lab_avg =
      totalinc_2030_baseline -
      rowSums(select(., c(inc2_2030_baseline,
                          inc3_2030_baseline)), na.rm = TRUE) +
      rowSums(select(
        ., c(inc2_2030_baseline_lab_avg,
             inc3_2030_baseline_lab_avg)), na.rm = TRUE),
    totalinc_2030_baseline_lab_max =
      totalinc_2030_baseline -
      rowSums(select(., c(inc2_2030_baseline,
                          inc3_2030_baseline)), na.rm = TRUE) +
      rowSums(select(
        ., c(inc2_2030_baseline_lab_max,
             inc3_2030_baseline_lab_max)), na.rm = TRUE)
  ) %>%
  mutate(
    totalinc_2030_baseline_lab_avg_coef =
      if_else(totalinc_2030_baseline == 0,
              1, totalinc_2030_baseline_lab_avg /
                totalinc_2030_baseline),
    totalinc_2030_baseline_lab_max_coef =
      if_else(totalinc_2030_baseline == 0,
              1, totalinc_2030_baseline_lab_max /
                totalinc_2030_baseline)
  ) %>%
  mutate(
    totalinc_2030_baseline_lab_avg_coef =
      if_else(is.na(totalinc_2030_baseline_lab_avg_coef),
              1, totalinc_2030_baseline_lab_avg_coef),
    totalinc_2030_baseline_lab_max_coef =
      if_else(is.na(totalinc_2030_baseline_lab_max_coef),
              1, totalinc_2030_baseline_lab_max_coef)
  )
```

We do the same for agriculture and livestock income alone

```r
ic_microsim_cc <- ic_microsim_cc %>%
  mutate(
    totalinc_2030_baseline_cc_avg =
      totalinc_2030_baseline -
      rowSums(select(., c(cropinc,
                            lvstk)), na.rm = TRUE) +
      rowSums(select(
        ., c(cropinc_2030_baseline_cc_avg,
             lvstk_2030_baseline_cc_avg)), na.rm = TRUE),
    totalinc_2030_baseline_cc_max =
      totalinc_2030_baseline -
      rowSums(select(., c(cropinc,
                            lvstk)), na.rm = TRUE) +
      rowSums(select(
        ., c(cropinc_2030_baseline_cc_max,
             lvstk_2030_baseline_cc_max)), na.rm = TRUE)
  ) %>%
  mutate(
    totalinc_2030_baseline_cc_avg_coef =
      if_else(totalinc_2030_baseline == 0,
              1, totalinc_2030_baseline_cc_avg
              / totalinc_2030_baseline),
    totalinc_2030_baseline_cc_max_coef =
      if_else(totalinc_2030_baseline == 0,
              1, totalinc_2030_baseline_cc_max
              / totalinc_2030_baseline)
  ) %>%
  mutate(
    totalinc_2030_baseline_cc_avg_coef =
      if_else(is.na(totalinc_2030_baseline_cc_avg_coef),
              1, totalinc_2030_baseline_cc_avg_coef),
    totalinc_2030_baseline_cc_max_coef =
      if_else(is.na(totalinc_2030_baseline_cc_max_coef),
              1, totalinc_2030_baseline_cc_max_coef)
  )
```

And yet again for the combined impacts

```
ic_microsim_cc <- ic_microsim_cc %>%
  mutate(
    totalinc_2030_baseline_lab_cc_avg =
      totalinc_2030_baseline -
      rowSums(select(., c(inc2_2030_baseline,
                            inc3_2030_baseline,
                            cropinc,
                            lvstk)), na.rm = TRUE) +
      rowSums(select(
        ., c(inc2_2030_baseline_lab_avg,
             inc3_2030_baseline_lab_avg,
             cropinc_2030_baseline_cc_avg,
             lvstk_2030_baseline_cc_avg)), na.rm = TRUE),
    totalinc_2030_baseline_lab_cc_max =
      totalinc_2030_baseline -
      rowSums(select(., c(inc2_2030_baseline,
                          inc3_2030_baseline,
                          cropinc,
                          lvstk)), na.rm = TRUE) +
      rowSums(select(
        ., c(inc2_2030_baseline_lab_max,
             inc3_2030_baseline_lab_max,
             cropinc_2030_baseline_cc_max,
             lvstk_2030_baseline_cc_max)), na.rm = TRUE)
  ) %>%
  mutate(
    totalinc_2030_baseline_lab_cc_avg_coef =
      if_else(totalinc_2030_baseline == 0,
              1, totalinc_2030_baseline_lab_cc_avg /
                totalinc_2030_baseline),
    totalinc_2030_baseline_lab_cc_max_coef =
      if_else(totalinc_2030_baseline == 0,
              1, totalinc_2030_baseline_lab_cc_max /
                totalinc_2030_baseline)
  ) %>%
  mutate(
    totalinc_2030_baseline_lab_cc_avg_coef =
      if_else(is.na(totalinc_2030_baseline_lab_cc_avg_coef),
              1, totalinc_2030_baseline_lab_cc_avg_coef),
    totalinc_2030_baseline_lab_cc_max_coef =
      if_else(is.na(totalinc_2030_baseline_lab_cc_max_coef),
              1, totalinc_2030_baseline_lab_cc_max_coef)
    )
```

We assume that the loss in income translates into a loss of expenditure.

```
income_losses <- ic_microsim_cc %>%
  select(interview__key,
         totalinc_2030_baseline_lab_avg_coef,
         totalinc_2030_baseline_lab_max_coef,
         totalinc_2030_baseline_cc_avg_coef,
         totalinc_2030_baseline_cc_max_coef,
         totalinc_2030_baseline_lab_cc_avg_coef,
         totalinc_2030_baseline_lab_cc_max_coef)


ca_microsim_cc <- ca_microsim %>%
  left_join(income_losses, join_by(hhid == interview__key))

# And now reduce total consumption

ca_microsim_cc <- ca_microsim_cc %>%
  mutate(totc_2030_baseline_lab_avg = totc_2030_baseline *
           totalinc_2030_baseline_lab_avg_coef,
         totc_2030_baseline_lab_max = totc_2030_baseline *
           totalinc_2030_baseline_lab_max_coef,
         totc_2030_baseline_cc_avg = totc_2030_baseline *
           totalinc_2030_baseline_cc_avg_coef,
         totc_2030_baseline_cc_max = totc_2030_baseline *
           totalinc_2030_baseline_cc_max_coef,
         totc_2030_baseline_lab_cc_avg = totc_2030_baseline *
           totalinc_2030_baseline_lab_cc_avg_coef,
         totc_2030_baseline_lab_cc_max = totc_2030_baseline *
           totalinc_2030_baseline_lab_cc_max_coef
         ) %>%
  mutate(aec_r_2030_baseline_lab_avg =
           totc_2030_baseline_lab_avg / ae_r / PI,
         aec_r_2030_baseline_lab_max =
           totc_2030_baseline_lab_max / ae_r / PI,
         aec_r_2030_baseline_cc_avg =
           totc_2030_baseline_cc_avg / ae_r / PI,
         aec_r_2030_baseline_cc_max =
           totc_2030_baseline_cc_max / ae_r / PI,
         aec_r_2030_baseline_lab_cc_avg =
           totc_2030_baseline_lab_cc_avg / ae_r / PI,
         aec_r_2030_baseline_lab_cc_max =
           totc_2030_baseline_lab_cc_max / ae_r / PI) %>%
  mutate(poor_2030_baseline_lab_avg =
           if_else(aec_r_2030_baseline_lab_avg < 52883, 1, 0),
         poor_2030_baseline_lab_max =
           if_else(aec_r_2030_baseline_lab_max < 52883, 1, 0),
         poor_2030_baseline_cc_avg =
            if_else(aec_r_2030_baseline_cc_avg < 52883, 1, 0),
          poor_2030_baseline_cc_max =
            if_else(aec_r_2030_baseline_cc_max < 52883, 1, 0),
          poor_2030_baseline_lab_cc_avg =
            if_else(aec_r_2030_baseline_lab_cc_avg < 52883, 1, 0),
          poor_2030_baseline_lab_cc_max =
            if_else(aec_r_2030_baseline_lab_cc_max < 52883, 1, 0)
          )

# We make a table to see who became poor.

test <- ca_microsim_cc %>%
  rename(poor_original = poor_Avpovln2022_2030_baseline,
         poor_cc = poor_2030_baseline_lab_avg) %>%
  group_by(income_decile_group, urb_rur) %>%
  summarize(no_hh = round(sum(weight_2030_nzs, na.rm = TRUE)),
            no_pp = round(sum(weight_2030_nzs * hhsize, na.rm = TRUE))) %>%
  ungroup()
```

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

```
test %>%
  gt()
```

income_decile_group	urb_rur	no_hh	no_pp
1	1	55581	101934
1	2	27908	74783
2	1	49717	97861
2	2	28239	77403
3	1	51846	125981
3	2	26300	84452
4	1	50737	138969
4	2	27163	106969
5	1	52779	181812
5	2	24816	104470
6	1	48955	178108
6	2	29091	130978
7	1	52818	202914
7	2	25175	115496

8	1	49690	209561
8	2	28184	137425
9	1	49603	225308
9	2	28665	151247
10	1	52287	245685
10	2	25319	141672

```
##write.table(test, "clipboard", sep="\t", row.names=FALSE)
```

0.8.3 Food prices

We start by looking at the differences of food prices between scenarios.

```
# We extract and reformat the price data
price_data <- macro_data %>%
  select(year, scenario_id, starts_with( c("fpi" , "epi") )) %>%
  rename(scenario = scenario_id) %>%
  pivot_longer(starts_with( c("fpi" , "epi") ),
               names_to = "type_decile",
               values_to = "index") %>%
  mutate(decile = parse_number(type_decile)) %>%
  mutate(commodity_group =
           case_when(
             str_starts(type_decile, "fpi") ~ "food",
             str_starts(type_decile, "epi") ~ "energy",
             TRUE ~ NA_character_
           )) %>%
  select(-type_decile) %>%
  relocate(index, .after = commodity_group)

# We take a look at price information in 2030
price_data %>%
  filter(year == 2030) %>%
  group_by(commodity_group, scenario) %>%
  summarize(index = mean(index, na.rm = TRUE)) %>%
  gt()
```

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

scenario	index
energy	
baseline	1.1291820
dry_hot	1.1248830
nzs	1.8014210
food	
baseline	1.0099860
dry_hot	1.0756960
nzs	0.9670056

So, we will assign a price index depending on which decile the household belonged to in the base year 2022. We will have a column for each scenario. So we manipulate our price data according to our years of interest (in this case, only 2030).

```r
# Filter `price_data` for the years of interest
price_data_yearsto <- price_data %>%
  filter(year %in% yearsto)

# Create a named vector for scenario indices
scenario_indices <- setNames(seq_along(scenarios), scenarios)

# Create the composite string column
price_data_yearsto <- price_data_yearsto %>%
  mutate(
    scenario_index = scenario_indices[scenario],
    composite_column = paste( scenario,year,commodity_group, sep = "_")
  ) %>%
  select(decile,index,composite_column)

composite_column_names <- unique(price_data_yearsto$composite_column)

price_data_yearsto <- price_data_yearsto %>%
  pivot_wider(names_from="composite_column", values_from = index)
```

So in this particular case, we don't want to use the price index from the `dry_hot` scenario, but we want to use the difference between the baseline and that scenario, so we are going to do those columns by hand, but we actually have to find a way to do it programmatically against the baseline.

```
price_data_yearsto <- price_data_yearsto %>%
  mutate(food_PI = dry_hot_2030_food - baseline_2030_food +1,
         energy_PI = nzs_2030_energy - baseline_2030_energy + 1)
```

And we join with our household's dataset.

```
# PP microsim already has decile information from previous join
ca_microsim_cc <- ca_microsim_cc %>%
  left_join(price_data_yearsto, join_by(decile==decile))
```

Since we don't have quantities for the aggregate food expenditure category or for the aggregate energy bundle, we assume a price of 1 in the survey year.

We will estimate price elasticities for a single "food" commodity from the consumption aggregate `FOOD_with_prices` dataset. We add decile data to the original.

```
food_summary <- food_with_prices %>%
  left_join(deciles, join_by(hhid))

# Step 1: Summarize the data at the household level
food_summary <- food_summary %>%
  group_by(hhid, decile) %>%
  summarize(
    total_quantity = sum(q, na.rm = TRUE),
    weighted_price = sum(avrpr_mean * q, na.rm = TRUE) / sum(q, na.rm = TRUE),
    .groups = 'drop'
  )

# Define a function to fit the model and extract the elasticity
fit_model <- function(data) {
  model <- lm(log(total_quantity) ~ log(weighted_price), data = data)
  coef(model)["log(weighted_price)"]
}

# Apply the model fitting function by decile
decile_models <- food_summary %>%
  group_by(decile) %>%
  nest() %>%
  mutate(price_elasticity = map_dbl(data, fit_model)) %>%
  select(decile, price_elasticity) %>%
  mutate(price_elasticity = if_else(price_elasticity >0,
                                    price_elasticity *(-1),
                                        price_elasticity))

decile_models
```

```
# A tibble: 10 x 2
# Groups:   decile [10]
   decile price_elasticity
    <dbl>            <dbl>
 1     10          -0.206
 2      8          -0.00939
 3      2          -0.360
 4      3          -0.428
 5      1          -0.483
 6      9          -0.118
 7      6          -0.116
 8      4          -0.299
 9      5          -0.253
10      7          -0.0598
```

Let's add back the elasticity data to the analysis dataset.

```
ca_microsim_cc <- ca_microsim_cc %>%
  left_join(decile_models, by = "decile")
```

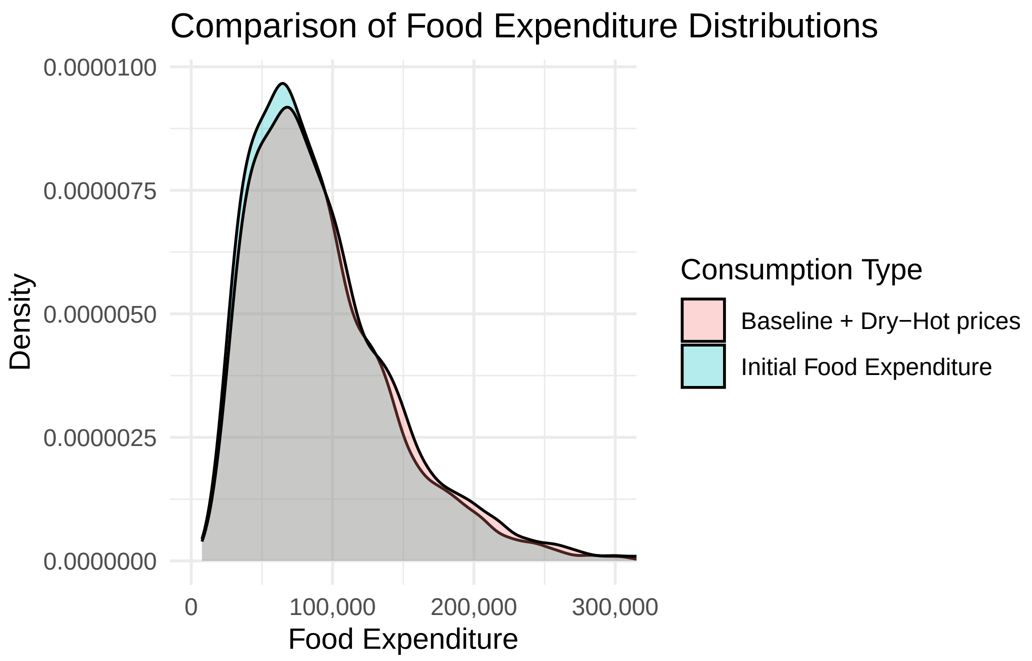
Let's apply the elasticities to the new data.

```
# Calculate the implicit price
# Assuming implicit_price can be calculated from the expenditure (food1)
# If we assume baseline quantity consumed is proportional to expenditure/price
ca_microsim_cc <- ca_microsim_cc %>%
  mutate(implicit_price = food1 / food1,  # This is 1 as we don't have baseline price
         food_quantity = food1 / implicit_price)

# Calculate the percentage change in prices for each decile
ca_microsim_cc <- ca_microsim_cc %>%
  mutate(food_1_dprice  = (baseline_2030_food - 1),
         food_2_dprice  = (dry_hot_2030_food - 1),
         food_PI_dprice = (food_PI - 1))

# Estimate the new food consumption levels
ca_microsim_cc <- ca_microsim_cc %>%
  mutate(
    food_q1_sim = food_quantity *
      (1 + food_1_dprice * price_elasticity),
    food_q2_sim = food_quantity *
      (1 + food_2_dprice * price_elasticity),
    food_qPI_sim = food_quantity *
      (1 + food_PI_dprice * price_elasticity))

# Calculate the new expenditure levels
ca_microsim_cc <- ca_microsim_cc %>%
  mutate(food_exp1_sim = food_q1_sim * baseline_2030_food,
         food_exp2_sim = food_q2_sim * dry_hot_2030_food,
         food_exp3_sim = food_qPI_sim * food_PI)

# View the results
print(ca_microsim_cc %>% select(decile, food1, baseline_2030_food, food_1_dprice, food_q1_si
```

```
# A tibble: 5,184 x 10
   decile   food1 baseline_2030_food food_1_dprice food_q1_sim food_exp1_sim
    <dbl>   <dbl>              <dbl>         <dbl>       <dbl>         <dbl>
 1      9  92178.               1.01       0.00973      92073.        92969.
 2      7 105290.               1.01       0.00963     105229.       106243.
 3      2  22733.               1.01       0.0102       22650.        22881.
 4      2 163379.               1.01       0.0102      162778.       164442.
 5      4 102718.               1.01       0.0104      102400.       103461.
 6     10 208995.               1.01       0.0104      208548.       210712.
 7      8 116151.               1.01       0.00995     116140.       117296.
 8      5  67911.               1.01       0.00965      67745.        68398.
 9      6 152144.               1.01       0.00978     151971.       153457.
10      8  80033.               1.01       0.00995      80025.        80822.
# i 5,174 more rows
# i 4 more variables: food_2_dprice <dbl>, food_q2_sim <dbl>,
#   food_exp2_sim <dbl>, food_PI_dprice <dbl>
```

Let's plot the distributions to see changes:

```
# Basic density plot comparing food1 and food_exp_sim
ggplot(ca_microsim_cc, aes(x = food1, fill = 'Initial Food Expenditure')) +
  geom_density(alpha = 0.3) +
  geom_density(
    data = ca_microsim_cc,
    aes(x = food_exp3_sim, fill = 'Baseline + Dry-Hot prices'),
    alpha = 0.3) +
  labs(
    fill = "Consumption Type",
    title = "Comparison of Food Expenditure Distributions",
    x = "Food Expenditure",
    y = "Density") +
  theme_minimal() +
  coord_cartesian(xlim = c(0, 300000)) + # Adjust the xlim for zoom
  scale_x_continuous(labels = scales::comma) +
  scale_y_continuous(labels = scales::comma)
```



Calculate losses in consumer surplus and purchasing power loss.

```
# Calculate Consumer Surplus loss for food1 and food2 scenarios
ca_microsim_cc <- ca_microsim_cc %>%
  mutate(
    across(
      c(food1,
        food_exp1_sim,
        food_exp2_sim,
        food_exp3_sim,
        totc_2030_baseline_lab_cc_avg), ~replace_na(., 0))) %>%
  mutate(food1_CSloss = ((food_quantity * implicit_price) /
                         totc_2030_baseline) * food_1_dprice * (
                           1 + (price_elasticity / 2) * food_1_dprice),
         food2_CSloss = ((food_quantity * implicit_price) /
                         totc_2030_dry_hot) * food_2_dprice * (
                           1 + (price_elasticity / 2) * food_2_dprice),
         foodPI_CSloss = ((food_quantity * implicit_price) /
                         totc_2030_baseline_lab_cc_avg) * food_PI_dprice * (
                           1 + (price_elasticity / 2) * food_PI_dprice),
         ttl_CSloss_1 = food1_CSloss,
         ttl_CSloss_2 = food2_CSloss,
         ttl_CSloss_PI = foodPI_CSloss)

# Calculate Purchasing Power loss for food1 and food2 and PI scenarios
ca_microsim_cc <- ca_microsim_cc %>%
  mutate(food1_PPloss = (food1 /
                         totc_2030_baseline) * food_1_dprice,
         food2_PPloss = (food1 /
                         totc_2030_dry_hot) * food_2_dprice,
         foodPI_PPloss = (food1 /
                          totc_2030_baseline_lab_cc_avg) * food_PI_dprice,
         ttl_PPloss_1 = food1_PPloss,
         ttl_PPloss_2 = food2_PPloss,
         ttl_PPloss_PI = foodPI_PPloss
         )

# Adjust total expenditure (totc) based on the purchasing power loss
ca_microsim_cc <- ca_microsim_cc %>%
  mutate(totc_2030_baseline_food1 = totc_2030_baseline * (1 - ttl_PPloss_1),
         totc_2030_dry_hot_food2 = totc_2030_dry_hot * (1 - ttl_PPloss_2),
         totc_2030_baseline_lab_cc_foodPI2 = totc_2030_baseline_lab_cc_avg * (1 - ttl_PPloss
         totc_2030_baseline_lab_cc_foodPI = totc_2030_baseline_lab_cc_avg - (food_exp3_sim -
         )

# View the results
print(ca_microsim_cc %>% select(decile, totc_2030_baseline, totc_2030_baseline_food1, totc_20
```

```
# A tibble: 5,184 x 5
   decile totc_2030_baseline totc_2030_baseline_food1 totc_2030_dry_hot_food2
    <dbl>              <dbl>                    <dbl>                   <dbl>
 1      9            298269.                  297372.                 291365.
 2      7            345611.                  344597.                 331885.
 3      2            130498.                    130266.                   126316.
 4      2            365825.                    364155.                   348536.
 5      4            285862.                    284798.                   272543.
 6     10            525030.                    522861.                   499583.
 7      8            232452.                    231296.                   223637.
 8      5            326731.                    326076.                   315638.
 9      6            479398.                    477910.                   458876.
10      8            197776.                    196980.                   188004.
# i 5,174 more rows
# i 1 more variable: totc_2030_baseline_lab_cc_foodPI <dbl>
```

Okay so now we estimate new welfare and poverty.

```r
ca_microsim_cc <- ca_microsim_cc %>%
  mutate(aec_r_2030_baseline_food1 = totc_2030_baseline_food1 / ae_r / PI,
         aec_r_2030_dry_hot_food2 = totc_2030_dry_hot_food2 / ae_r / PI,
         aec_r_2030_baseline_foodPI = totc_2030_baseline_lab_cc_foodPI / ae_r / PI) %>%
  mutate(poor_2030_baseline_food1 =
           if_else(aec_r_2030_baseline_food1 < 52883, 1, 0),
         poor_2030_dry_hot_food2 =
           if_else(aec_r_2030_dry_hot_food2 < 52883, 1, 0),
         poor_2030_baseline_lab_cc_foodPI =
           if_else(aec_r_2030_baseline_foodPI < 52883, 1, 0))
```

And now we see who became poor

```r
# We make a table to see who became poor.
test <- ca_microsim_cc

test <- test%>%
  rename(poor_original = poor_Avpovln2022_2030_baseline,
         poor_cc = poor_2030_baseline_lab_cc_avg,
         poor_food1 = poor_2030_baseline_food1,
         poor_food2 = poor_2030_dry_hot_food2,
         poor_foodPI =  poor_2030_baseline_lab_cc_foodPI) %>%
  group_by(poor_original) %>%
  summarize(no_hh = round(sum(weight_2030_baseline, na.rm = TRUE)),
            no_pp = round(sum(weight_2030_baseline*hhsize, na.rm = TRUE)))

test %>%
  gt()
```

poor_original	no_hh	no_pp
0	697740	2412949
1	85849	420079

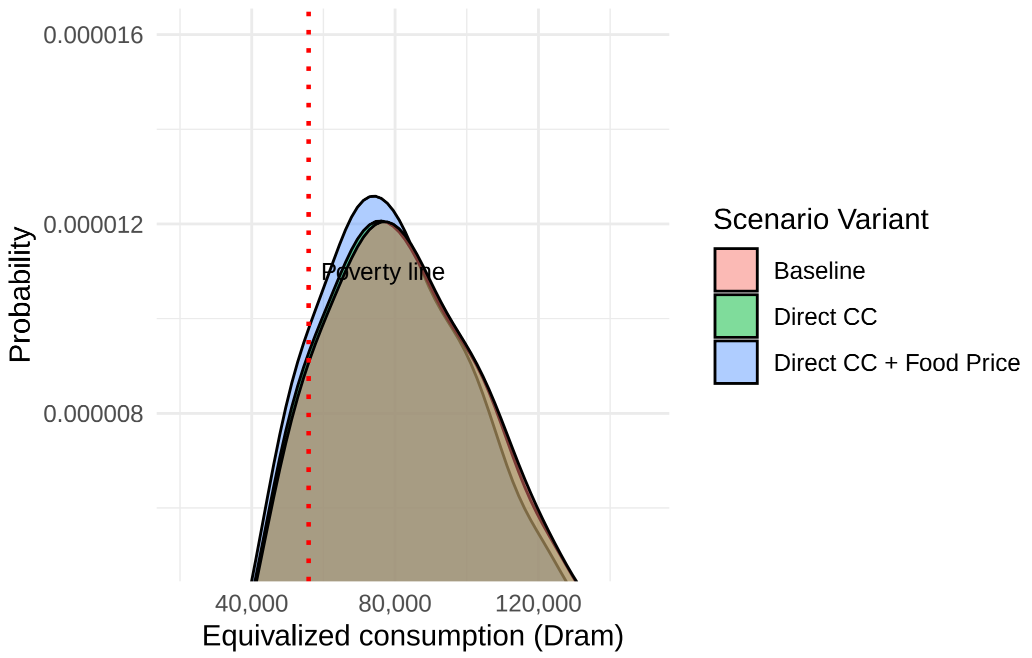
```
##write.table(test, "clipboard", sep="\t", row.names=FALSE)
```

And we map these results.

```
# foodpoor <- ca_microsim_cc %>%
#   mutate(new_poor_food_base = if_else(
#     poor_cc_avg_food2 == 1 & poor_cc_avg == 0, 1, 0),
#          new_poor_food_dryhot = if_else(
#            poor_cc_avg_food1 == 1 & poor_cc_avg == 0, 1, 0),
#     NAM_1 = as_factor(marz)) %>%
#   mutate(NAM_1 = if_else(NAM_1 == "VayotsDzor", "Vayots Dzor", NAM_1)) %>%
#   mutate(NAM_1 = if_else(NAM_1 == "Sjunik", "Syunik", NAM_1)) %>%
#   select(NAM_1, poor_Avpovln2022, poor_cc_avg, poor_cc_max,
#          poor_cc_avg_food1, poor_cc_avg_food2, new_poor_food_base,
#          new_poor_food_dryhot, weight, hhsize)
#
# fp <-foodpoor %>%
#   group_by(NAM_1) %>%
#   summarize(new_poor = round(sum(new_poor_food_dryhot * weight*hhsize, na.rm = TRUE))) %>%
#   mutate(label = paste0(NAM_1," (", new_poor, ")"))
#
#
# ##write.table(fp, "clipboard", sep="\t", row.names=FALSE)
# fp_map <- adm1 |>
#   left_join(fp, join_by(NAM_1 == NAM_1))
#
# fp_map <-tm_shape(fp_map)+
#   tm_polygons("new_poor", legend.show = FALSE) +
#   tm_text("label", size = .7, col = "black")+
#   tm_layout(legend.position = c("right", "top"),
#             title= "Additional Poor Dry-Hot Scenario",
#             title.position = c('left', 'bottom'),
#             title.size = 0.9)
#
# fp_map
```

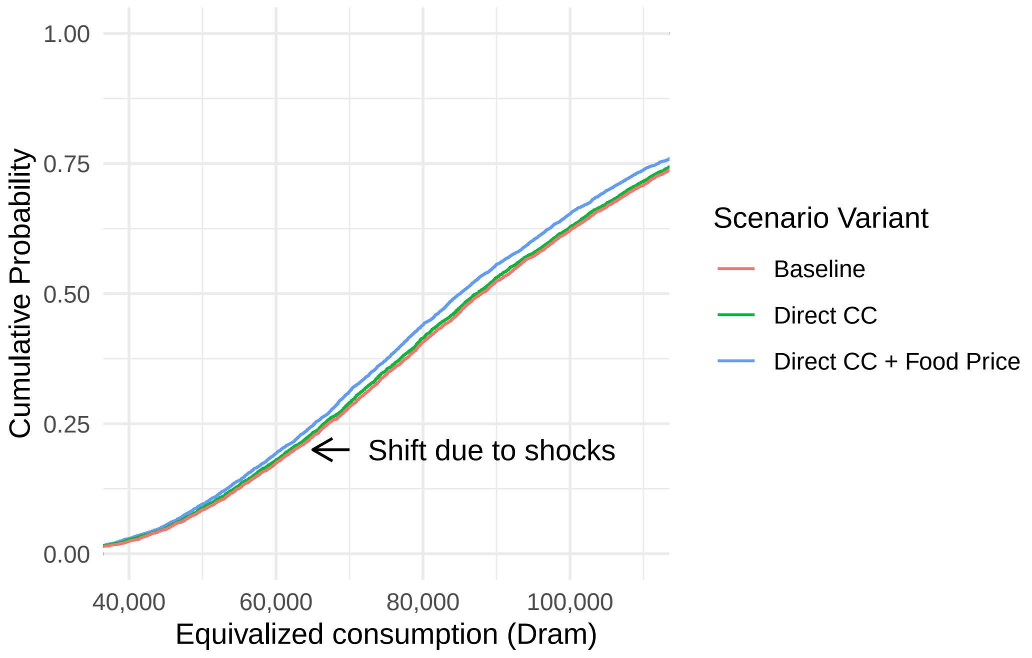
Let's plot how the distribution moves with all these measures.

```
# Basic density plot comparing equivalized consumption per capita
ggplot(ca_microsim_cc,
       aes(x = aec_r_2030_baseline_foodPI, fill = 'Direct CC + Food Price')) +
  geom_density(alpha = 0.5) +
  # geom_density(
  #   data = ca_microsim_cc,
  #   aes(x = aec_r_2030_dry_hot, fill = 'Dry/Hot'),
  #   alpha = 0.5) +
  # geom_density(
  #   data = ca_microsim_cc,
  #   aes(x = aec_r_2030_dry_hot_food2, fill = 'Dry/Hot + Food Price'),
  #   alpha = 0.5) +
  geom_density(
    data = ca_microsim_cc,
    aes(x = aec_r_2030_baseline_lab_cc_avg, fill = 'Direct CC'),
    alpha = 0.5) +
  geom_density(
    data = ca_microsim_cc,
    aes(x = aec_r_2030_baseline, fill = 'Baseline'),
    alpha = 0.5) +
  labs(
    fill = "Scenario Variant",
    # title = "Comparison of Consumption Distributions",
    x = "Equivalized consumption (Dram)",
    y = "Probability") +
  theme_minimal()+
  coord_cartesian(xlim = c(20000, 150000),
                  ylim = c(0.000005,0.0000160)) + # Zoom in without removing data
  scale_x_continuous(labels = scales::comma) +
  scale_y_continuous(labels = scales::comma)+
  geom_vline(xintercept = 55883,
             color = "red",
             linetype = "dotted",
             linewidth =0.8) +
  annotate("text",
           x = 55883,
           y = 0.0000110,
           #label = "Poverty line\nAMD 55,883",
           label = "Poverty line",
           color = "black",
           hjust = -0.1,
           # vjust = -3.5,
           #angle = 90,
           size = 3)
```



And we also plot the cumulative distributions.

```
# Plot the cumulative distribution with left-facing arrows
ggplot(ca_microsim_cc,
       aes(x = aec_r_2030_baseline_foodPI, color = 'Direct CC + Food Price')) +
  stat_ecdf(geom = "step") +
  # stat_ecdf(data = ca_microsim_cc,
  #           aes(x = aec_r_2030_baseline_lab_avg, color = 'Baseline + Labor Productivity'))
  stat_ecdf(data = ca_microsim_cc,
            aes(x = aec_r_2030_baseline_lab_cc_avg, color = 'Direct CC')) +
  stat_ecdf(data = ca_microsim_cc,
            aes(x = aec_r_2030_baseline, color = 'Baseline')) +
  labs(
    color = "Scenario Variant",
    # title = "Comparison of Cumulative Consumption Distributions",
    x = "Equivalized consumption (Dram)",
    y = "Cumulative Probability") +
  theme_minimal() +
  coord_cartesian(xlim = c(40000, 110000)) +
  scale_x_continuous(labels = scales::comma) +
  # geom_vline(xintercept = 55883,
  #             color = "red",
  #             linetype = "dotted",
  #             linewidth = 0.8) +
  # annotate("text",
  #           x = 55883,
  #           y = 0.5,
  #           label = "Poverty line",
  #           color = "black",
  #           hjust = -0.1,
  #           size = 3) +
  annotate("segment", x = 70000, xend = 65000, y = 0.2, yend = 0.2,
           arrow = arrow(length = unit(0.3, "cm")), color = "black") +
  annotate("text", x = 72500, y = 0.2, label = "Shift due to shocks", hjust = 0)
```



```
# annotate("segment", x = 80000, xend = 75000, y = 0.4, yend = 0.4,
#           arrow = arrow(length = unit(0.3, "cm")), color = "black") +
# annotate("text", x = 82500, y = 0.4, label = "Shift due to shocks", hjust = 0)
```

0.8.4 Energy prices

We first establish energy elasticities. We only have quantities for liquefied gas `hous_29_a` and their purchase value `hous_29_b` with which we can compute price. Unfortunately there is no quantity for electricity, so we will use the same elasticity. We do not compute an elasticity by decile, because there are too few observations per decile, so we estimate an overall elasticity for all the distribution.

```
# We extract the liquefied gas (hous_29), natural gas (hous_38)
# and electricity (hous_23) information
energy_summary_all <- hh %>%
  mutate(l_gas_price =
           if_else(hous_29_a == 0, 0, hous_29_b/hous_29_a),
         n_gas_price =
           if_else(hous_36_a == 0, 0, hous_36_b/hous_36_a)) %>%
  select(interview__key, weight, hous_29_a, hous_29_b,hous_23,
         hous_36_a, hous_36_b, l_gas_price, n_gas_price)

# We estimate the weighted mean of liquefied gas prices
avg_l_gas_price <- weighted.mean(energy_summary_all$l_gas_price,
                                 energy_summary_all$weight,
                                 na.rm=TRUE)

# And do the same for natural gas
avg_n_gas_price <- weighted.mean(energy_summary_all$n_gas_price,
                                 energy_summary_all$weight,
                                 na.rm=TRUE)

# We replace missing 0 values with average gas price
energy_summary_all <- energy_summary_all %>%
  mutate(l_gas_price = if_else(l_gas_price==0.0,
                             avg_l_gas_price,
                             l_gas_price),
         n_gas_price = if_else(n_gas_price==0.0,
                             avg_n_gas_price,
                             n_gas_price))

# We subset to compute a single elasticity value for the entire distribution
# Summarize the data at the household level
l_energy_summary <- energy_summary_all %>%
  filter(!is.na(l_gas_price))# %>%

# Filter out rows with non-positive values in hous_29_a or l_gas_price
```

```
l_energy_summary <- l_energy_summary[l_energy_summary$hous_29_a > 0 & l_energy_summary$l_gas_

# Compute the log of quantity and price
l_energy_summary$log_gas_quantity <- log(l_energy_summary$hous_29_a)
l_energy_summary$log_l_gas_price <- log(l_energy_summary$l_gas_price)

# Estimate a single price elasticity for the entire dataset
model <- lm(log_gas_quantity ~ log_l_gas_price, data = l_energy_summary)
summary_model <- summary(model)

# Extract the price elasticity (coefficient of log_l_gas_price)
l_gas_price_elasticity <- coef(summary_model)["log_l_gas_price", "Estimate"]

# Print the results
print(summary_model)
```

```

Call:
lm(formula = log_gas_quantity ~ log_l_gas_price, data = l_energy_summary)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.79267 -0.42107 -0.01872  0.50991  1.87661 

Coefficients:
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)      2.33837    0.63292   3.695  0.00025 ***
log_l_gas_price -0.08781    0.10115  -0.868  0.38587    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5834 on 412 degrees of freedom
Multiple R-squared:  0.001826,	Adjusted R-squared:  -0.0005972 
F-statistic: 0.7535 on 1 and 412 DF,  p-value: 0.3859
```

```
print(paste("Estimated price elasticity of gas quantity demanded:", l_gas_price_elasticity))
```

```
[1] "Estimated price elasticity of gas quantity demanded: -0.0878078581985716"
```

We see that this commodity is highly inelastic at -0.088781.The estimated price elasticity of -0.086 suggests that the demand for gas is inelastic. This means that a 1% increase in the price of gas would lead to only a 0.09% decrease in the quantity of gas demanded. The absolute value of the elasticity is much less than 1, indicating that consumers do not significantly reduce their gas consumption in response to price increases. This could be because gas is a necessity for many households, and they cannot easily reduce their usage or switch to alternative sources. We expect electricity, being so universal in the dataset to behave in the same manner. We wanted to use natural gas to compute a similar metric, but there is hardly any variation in prices. Everybody experiences the same price and so there is not enough variation to compute a valid model. We will use the elasticity from liquefied gas for our purposes.

Let's add back the elasticity data to the analysis dataset.

```r
ca_microsim_cc$l_gas_price_elasticity <- l_gas_price_elasticity
ca_microsim_cc <- ca_microsim_cc %>%
  left_join(energy_summary_all, join_by(hhid==interview__key))
```

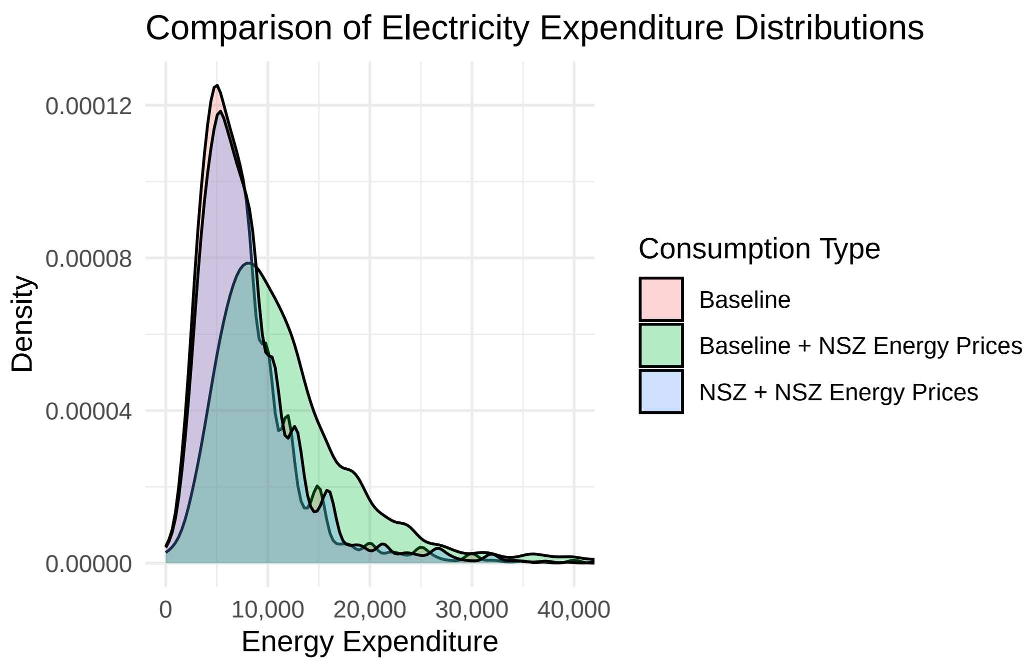
Let's apply the elasticities to the new data.

```r
# Calculate the implicit price
# Assuming implicit_price can be calculated from the expenditure
# If we assume baseline quantity consumed is proportional to expenditure/price
ca_microsim_cc <- ca_microsim_cc %>%
  mutate(
    # This is 1 as we don't have baseline price
    electricity_implicit_price = if_else(hous_23 == 0,1,hous_23 / hous_23),
    electricity_quantity = hous_23 / electricity_implicit_price,
    energy_price_elasticity = l_gas_price_elasticity)

EM_elec_price <- 1.071353 # Price increase in Energy Model
EM_gas_price <- 1.025514

# Calculate the percentage change in prices by decile
ca_microsim_cc <- ca_microsim_cc %>%
  mutate(energy_baseline_dprice  = (energy_PI - 1),
         energy_nzs_dprice = (nzs_2030_energy - 1),
         EM_elec_dprice = (EM_elec_price-1), # Interpolation from Energy Model
         EM_gas_dprice = (EM_gas_price-1))

# Estimate the new energy consumption levels
ca_microsim_cc <- ca_microsim_cc %>%
  mutate(
    electricity_baseline_q_sim = electricity_quantity *
      (1 + energy_baseline_dprice * energy_price_elasticity),
    electricity_nzs_q_sim = electricity_quantity *
```

```
      (1 + energy_nzs_dprice * energy_price_elasticity),
    electricity_EM_q_sim = electricity_quantity *
      (1 + EM_elec_dprice * energy_price_elasticity),
    l_gas_baseline_q_sim = hous_29_a *
      (1 + energy_baseline_dprice * energy_price_elasticity),
    l_gas_nzs_q_sim = hous_29_a *
      (1 + energy_nzs_dprice * energy_price_elasticity),
    l_gas_EM_q_sim = hous_29_a *
      (1 + EM_gas_dprice * energy_price_elasticity),
    n_gas_baseline_q_sim = hous_36_a *
      (1 + energy_baseline_dprice * energy_price_elasticity),
    n_gas_nzs_q_sim = hous_36_a *
      (1 + energy_nzs_dprice * energy_price_elasticity),
    n_gas_EM_q_sim = hous_36_a *
      (1 + EM_gas_dprice * energy_price_elasticity)
    )

# Calculate the new expenditure levels
ca_microsim_cc <- ca_microsim_cc %>%
  mutate(electricity_baseline_sim =
           electricity_baseline_q_sim * energy_PI, #because e-price = 1
         l_gas_baseline_sim =
           l_gas_baseline_q_sim * l_gas_price * energy_PI,
         n_gas_baseline_sim =
           n_gas_baseline_q_sim * n_gas_price * energy_PI,
         electricity_nzs_sim =
           electricity_nzs_q_sim * nzs_2030_energy,#because e-price = 1
         l_gas_nzs_sim =
           l_gas_nzs_q_sim * l_gas_price * nzs_2030_energy,
         n_gas_nzs_sim =
           n_gas_nzs_q_sim * n_gas_price * nzs_2030_energy,
         electricity_EM_sim =
           electricity_EM_q_sim * EM_elec_price,#because e-price = 1
         l_gas_EM_sim =
           l_gas_EM_q_sim * l_gas_price * EM_gas_price,
         n_gas_EM_sim =
           n_gas_EM_q_sim * n_gas_price * EM_gas_price)
```

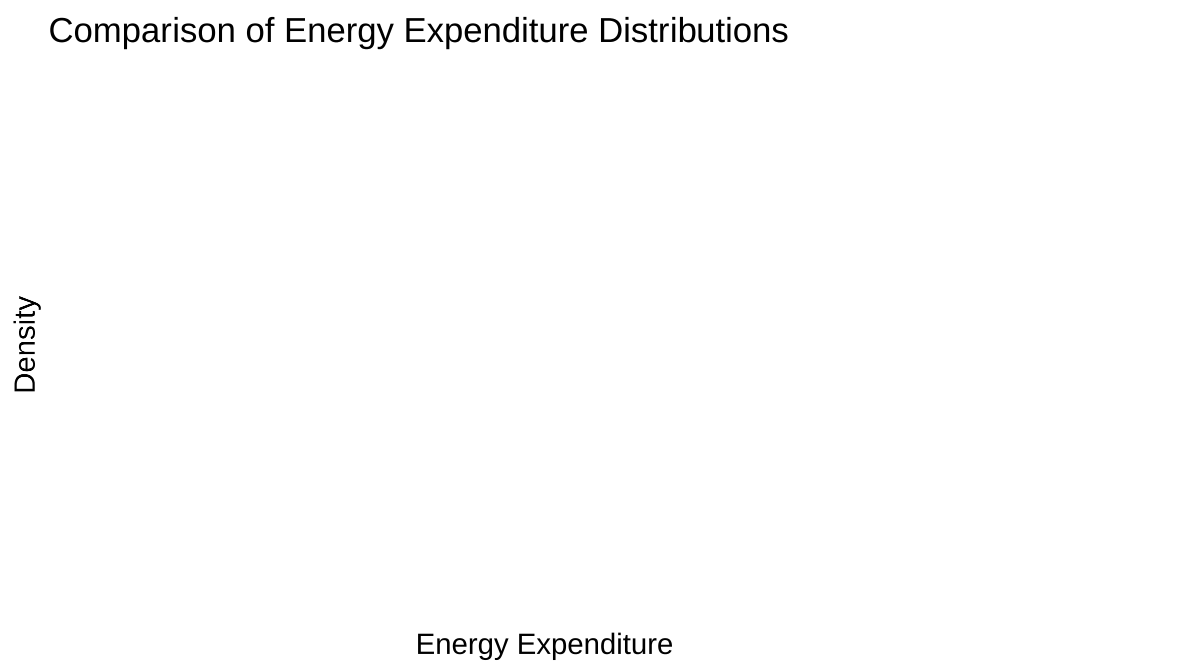
Let's plot the distributions to see changes:

```r
# Basic density plot comparing food1 and food_exp_sim
ggplot(ca_microsim_cc, aes(x =  hous_23, fill = 'Baseline')) +
  geom_density(alpha = 0.3) +
  geom_density(
    data = ca_microsim_cc,
    aes(x = electricity_baseline_sim, fill = 'Baseline + NSZ Energy Prices'),
    alpha = 0.3) +
   geom_density(
    data = ca_microsim_cc,
    aes(x = electricity_EM_sim, fill = 'NSZ + NSZ Energy Prices'),
    alpha = 0.3) +
  #facet_wrap(~decile)+
  labs(
    fill = "Consumption Type",
    title = "Comparison of Electricity Expenditure Distributions",
    x = "Energy Expenditure",
    y = "Density") +
  theme_minimal() +
  coord_cartesian(xlim = c(0, 40000)) + # Adjust the xlim for zoom
  scale_x_continuous(labels = scales::comma) +
  scale_y_continuous(labels = scales::comma)
```



```r
# Basic density plot comparing food1 and food_exp_sim
ggplot(ca_microsim_cc, aes(x =  hous_23+hous_29_b+hous_36_b, fill = 'Baseline')) +
  geom_density(alpha = 0.3) +
  geom_density(
    data = ca_microsim_cc,
    aes(x = electricity_baseline_sim+l_gas_baseline_sim+n_gas_baseline_sim, fill = 'Baseline
    alpha = 0.3) +
   geom_density(
    data = ca_microsim_cc,
    aes(x = electricity_nzs_sim+l_gas_nzs_sim+n_gas_nzs_sim, fill = 'NSZ + NSZ Energy Prices
    alpha = 0.3) +
  # facet_wrap(~decile)+
  labs(
    fill = "Consumption Type",
    title = "Comparison of Energy Expenditure Distributions",
    x = "Energy Expenditure",
    y = "Density") +
  theme_minimal() +
  coord_cartesian(xlim = c(0, 100000)) + # Adjust the xlim for zoom
  scale_x_continuous(labels = scales::comma) +
  scale_y_continuous(labels = scales::comma)
```

```
Warning: Removed 5184 rows containing non-finite outside the scale range
(`stat_density()`).
Removed 5184 rows containing non-finite outside the scale range
(`stat_density()`).
Removed 5184 rows containing non-finite outside the scale range
(`stat_density()`).
```



Calculate losses in consumer surplus and purchasing power loss.

```r
# Calculate Purchasing Power loss for food1 and food2 and PI scenarios
ca_microsim_cc <- ca_microsim_cc %>%
  mutate(
    across(
      c(hous_23,
        hous_29_b,
        hous_36_b,
        totc_2030_baseline,
        totc_2030_nzs,
        l_gas_baseline_sim,
        n_gas_baseline_sim,
        electricity_baseline_sim,
        l_gas_nzs_sim,
        n_gas_nzs_sim,
        electricity_nzs_sim,
        l_gas_EM_sim,
        n_gas_EM_sim,
        electricity_EM_sim), ~replace_na(., 0))) %>%
  mutate(energy_baseline_PPloss = ((hous_23 + hous_29_b + hous_36_b) /
                           totc_2030_baseline) * energy_baseline_dprice,
         energy_nzs_PPloss = ((hous_23 + hous_29_b + hous_36_b) /
                            totc_2030_nzs) * energy_nzs_dprice,
         ttl_PPloss_1 = energy_baseline_PPloss,
         ttl_PPloss_2 = energy_nzs_PPloss
         )

# Adjust total expenditure (totc) based on the purchasing power loss
ca_microsim_cc <- ca_microsim_cc %>%
  # mutate(nzs_scale_coef = if_else(
  #   totc_2030_baseline==0, 1, totc_2030_nzs/totc_2022)) %>%
  mutate(#totc_2030_baseline_energy2 = totc_2030_baseline * (1 - ttl_PPloss_1),
         totc_2030_baseline_energy =
           totc_2030_baseline -
           ((electricity_baseline_sim +
               l_gas_baseline_sim +
               n_gas_baseline_sim) -
              (hous_23 +
                 hous_36_b +
                 hous_29_b)),
         #totc_2030_nzs_energy2 = totc_2030_nzs * (1 - ttl_PPloss_2),
         totc_2030_nzs_energy =
           totc_2030_nzs -
           ((electricity_nzs_sim +
               l_gas_nzs_sim +
               n_gas_nzs_sim) -
              (hous_23 +
                 hous_36_b +
                 hous_29_b)),
         totc_2030_EM_baseline_energy =
           totc_2030_baseline -
           ((electricity_EM_sim +
               l_gas_EM_sim +
               n_gas_EM_sim) -
              (hous_23 +
                 hous_36_b +
                 hous_29_b)),
         totc_2030_EM_nzs_energy =
           totc_2030_nzs -
           ((electricity_EM_sim +
               l_gas_EM_sim +
               n_gas_EM_sim) -
              (hous_23 +
                 hous_36_b +
                 hous_29_b))
         )

# View the results
print(ca_microsim_cc %>% select(decile, totc_2030_baseline, totc_2030_baseline_energy, totc_
```

```
# A tibble: 5,184 x 6
   decile totc_2030_baseline totc_2030_baseline_energy totc_2030_nzs_energy
    <dbl>              <dbl>                     <dbl>                <dbl>
 1      9            298269.                   250374.              242384.
 2      7            345611.                   326156.              297259.
 3      2            130498.                   128170.              120539.
 4      2            365825.                   332689.              305466.
 5      4            285862.                   261819.              234343.
 6     10            525030.                   484825.              438545.
 7      8            232452.                   203798.              203659.
 8      5            326731.                   294705.              262852.
 9      6            479398.                   439146.              395652.
10      8            197776.                   185229.              167076.
# i 5,174 more rows
# i 2 more variables: totc_2030_EM_baseline_energy <dbl>,
#   totc_2030_EM_nzs_energy <dbl>
```

Okay so now we estimate new welfare and poverty.

```
ca_microsim_cc <- ca_microsim_cc %>%
  mutate(aec_r_2030_baseline_energy = totc_2030_baseline_energy / ae_r / PI,
         aec_r_2030_nzs_energy = totc_2030_nzs_energy / ae_r / PI,
         aec_r_2030_EM_baseline_energy =
           totc_2030_EM_baseline_energy / ae_r / PI,
         aec_r_2030_EM_nzs_energy =
           totc_2030_EM_nzs_energy / ae_r / PI) %>%
  mutate(poor_2030_baseline_energy =
           if_else(aec_r_2030_baseline_energy < 52883, 1, 0),
         poor_2030_nzs_energy =
           if_else(aec_r_2030_nzs_energy < 52883, 1, 0),
         poor_2030_EM_baseline_energy =
           if_else(aec_r_2030_EM_baseline_energy < 52883, 1, 0),
         poor_2030_EM_nzs_energy =
           if_else(aec_r_2030_EM_nzs_energy < 52883, 1, 0))
```

And now we see who became poor

```r
# We make a table to see who became poor.
test <- ca_microsim_cc

test <- test%>%
  rename(poor_original = poor_Avpovln2022_2030_baseline,
         poor_baseline_energy = poor_2030_baseline_energy
         ) %>%
  group_by(poor_original) %>%
  summarize(no_hh = round(sum(weight_2030_baseline, na.rm = TRUE)),
            no_pp = round(sum(weight_2030_baseline*hhsize, na.rm = TRUE)))

test %>%
  gt()
```

poor_original	no_hh	no_pp
0	697740	2412949
1	85849	420079

```r
#write.table(test, "clipboard", sep="\t", row.names=FALSE)
```

And we map these results.

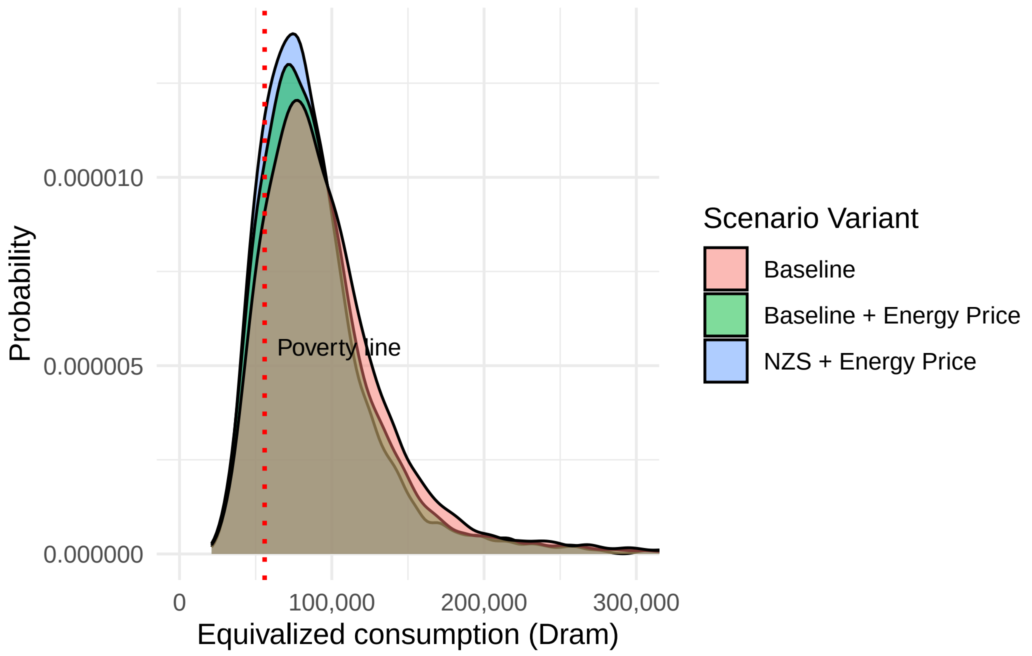
```r
# foodpoor <- ca_microsim_cc %>%
#   mutate(new_poor_food_base = if_else(
#     poor_cc_avg_food2 == 1 & poor_cc_avg == 0, 1, 0),
#          new_poor_food_dryhot = if_else(
#            poor_cc_avg_food1 == 1 & poor_cc_avg == 0, 1, 0),
#     NAM_1 = as_factor(marz)) %>%
#   mutate(NAM_1 = if_else(NAM_1 == "VayotsDzor", "Vayots Dzor", NAM_1)) %>%
#   mutate(NAM_1 = if_else(NAM_1 == "Sjunik", "Syunik", NAM_1)) %>%
#   select(NAM_1, poor_Avpovln2022, poor_cc_avg, poor_cc_max,
#          poor_cc_avg_food1, poor_cc_avg_food2, new_poor_food_base,
#          new_poor_food_dryhot, weight, hhsize)
#
# fp <-foodpoor %>%
#   group_by(NAM_1) %>%
#   summarize(new_poor = round(sum(new_poor_food_dryhot * weight*hhsize, na.rm = TRUE))) %>%
#   mutate(label = paste0(NAM_1," (", new_poor, ")"))
```

```
#
#
# ##write.table(fp, "clipboard", sep="\t", row.names=FALSE)
# fp_map <- adm1 |>
#   left_join(fp, join_by(NAM_1 == NAM_1))
#
# fp_map <-tm_shape(fp_map)+
#   tm_polygons("new_poor", legend.show = FALSE) +
#   tm_text("label", size = .7, col = "black")+
#   tm_layout(legend.position = c("right", "top"),
#             title= "Additional Poor Dry-Hot Scenario",
#             title.position = c('left', 'bottom'),
#             title.size = 0.9)
#
# fp_map
```

Let's plot how the distribution moves with all these measures.

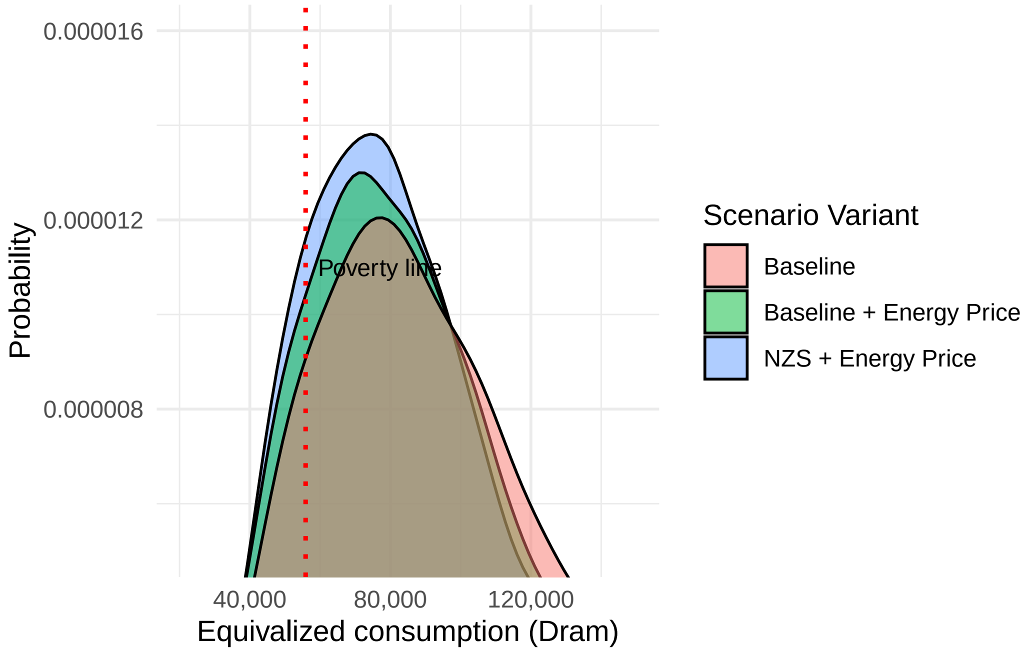
Food prices

```
# Basic density plot comparing equivalized consumption per capita
ggplot(ca_microsim_cc,
       aes(x = aec_r_2030_nzs_energy, fill = 'NZS + Energy Price')) +
  geom_density(alpha = 0.5) +
  # geom_density(
  #   data = ca_microsim_cc,
  #   aes(x = aec_r_2030_dry_hot, fill = 'Dry/Hot'),
  #   alpha = 0.5) +
  geom_density(
    data = ca_microsim_cc,
    aes(x = aec_r_2030_baseline_energy, fill = 'Baseline + Energy Price'),
    alpha = 0.5) +
  # geom_density(
  #   data = ca_microsim_cc,
  #   aes(x = aec_r_2030_baseline_lab_cc_avg, fill = 'Direct CC'),
  #   alpha = 0.5) +
  geom_density(
    data = ca_microsim_cc,
    aes(x = aec_r_2030_baseline, fill = 'Baseline'),
    alpha = 0.5) +
  labs(
    fill = "Scenario Variant",
    # title = "Comparison of Consumption Distributions",
    x = "Equivalized consumption (Dram)",
    y = "Probability") +
  theme_minimal()+
  coord_cartesian(xlim = c(00000, 300000))+
                  # ylim = c(0.000005,0.0000160)) + # Zoom in without removing data
  scale_x_continuous(labels = scales::comma) +
  scale_y_continuous(labels = scales::comma)+
  geom_vline(xintercept = 55883,
             color = "red",
             linetype = "dotted",
             linewidth =0.8) +
  annotate("text",
           x = 55883,
           y = 0.0000055,
           #label = "Poverty line\nAMD 55,883",
           label = "Poverty line",
           color = "black",
           hjust = -0.1,
           # vjust = -3.5,
           #angle = 90,
           size = 3)
```



Energy

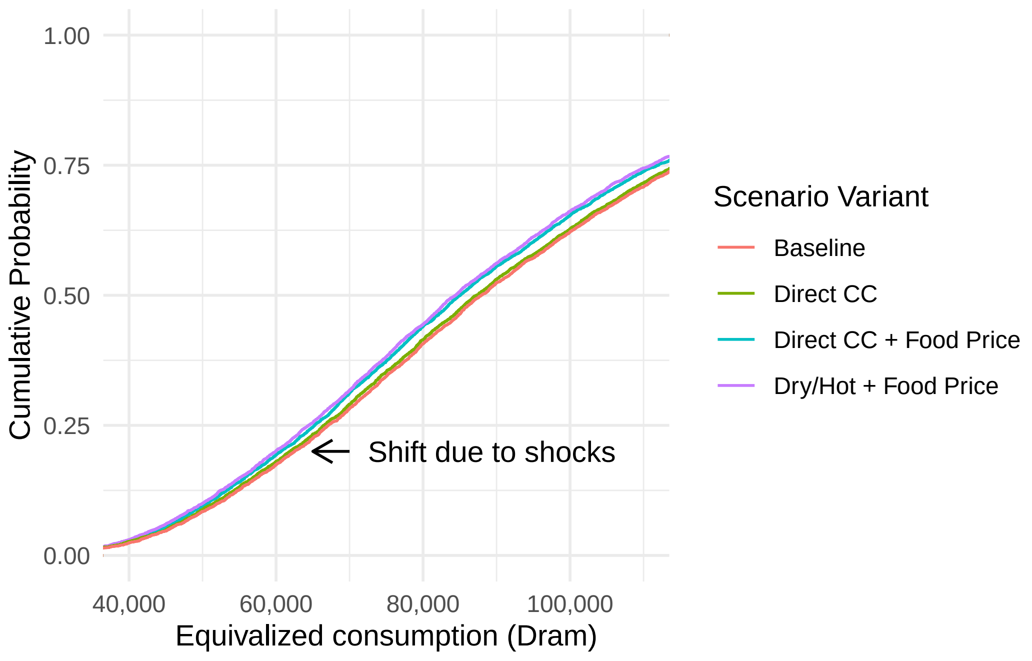
```r
# Basic density plot comparing equivalized consumption per capita
ggplot(ca_microsim_cc,
       aes(x = aec_r_2030_nzs_energy, fill = 'NZS + Energy Price')) +
  geom_density(alpha = 0.5) +
  # geom_density(
  #   data = ca_microsim_cc,
  #   aes(x = aec_r_2030_dry_hot, fill = 'Dry/Hot'),
  #   alpha = 0.5) +
  geom_density(
    data = ca_microsim_cc,
    aes(x = aec_r_2030_baseline_energy, fill = 'Baseline + Energy Price'),
    alpha = 0.5) +
  # geom_density(
  #   data = ca_microsim_cc,
  #   aes(x = aec_r_2030_baseline_lab_cc_avg, fill = 'Direct CC'),
  #   alpha = 0.5) +
  geom_density(
    data = ca_microsim_cc,
    aes(x = aec_r_2030_baseline, fill = 'Baseline'),
    alpha = 0.5) +
  labs(
    fill = "Scenario Variant",
    # title = "Comparison of Consumption Distributions",
    x = "Equivalized consumption (Dram)",
    y = "Probability") +
  theme_minimal()+
  coord_cartesian(xlim = c(20000, 150000),
                  ylim = c(0.000005,0.0000160)) + # Zoom in without removing data
  scale_x_continuous(labels = scales::comma) +
  scale_y_continuous(labels = scales::comma)+
  geom_vline(xintercept = 55883,
             color = "red",
             linetype = "dotted",
             linewidth =0.8) +
  annotate("text",
           x = 55883,
           y = 0.0000110,
           #label = "Poverty line\nAMD 55,883",
           label = "Poverty line",
           color = "black",
           hjust = -0.1,
           # vjust = -3.5,
           #angle = 90,
           size = 3)
```



And we also plot the cumulative distributions.

For food prices and cc

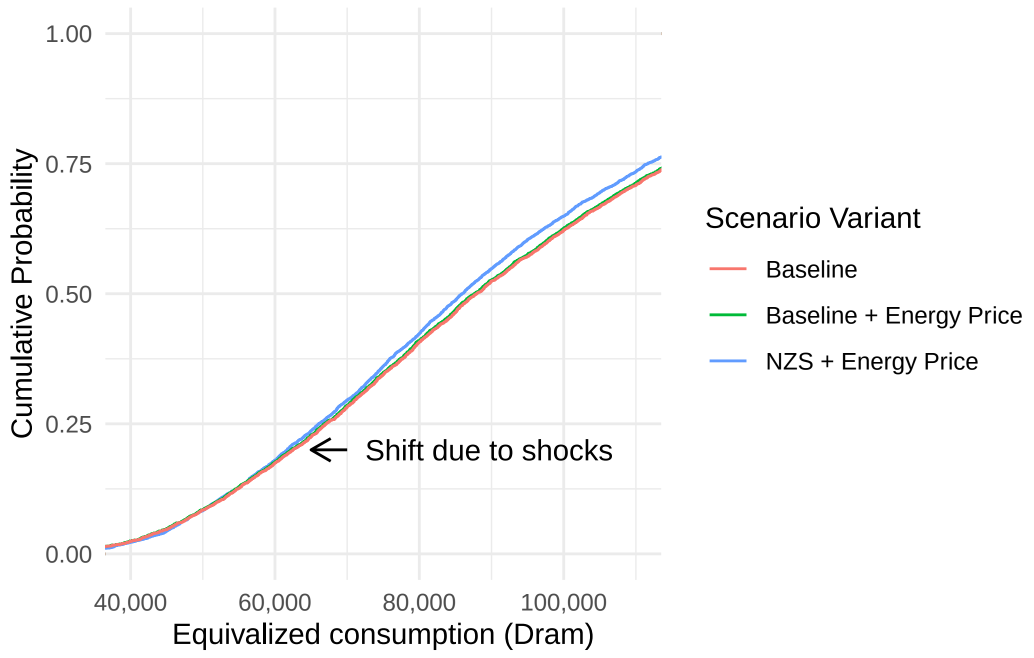
```
# Plot the cumulative distribution with left-facing arrows
ggplot(ca_microsim_cc,
       aes(x = aec_r_2030_baseline_foodPI, color = 'Direct CC + Food Price')) +
  stat_ecdf(geom = "step") +
  # stat_ecdf(data = ca_microsim_cc,
  #           aes(x = aec_r_2030_baseline_lab_avg, color = 'Baseline + Labor Productivity'))
  stat_ecdf(data = ca_microsim_cc,
            aes(x = aec_r_2030_dry_hot_food2, color = 'Dry/Hot + Food Price')) +
  stat_ecdf(data = ca_microsim_cc,
            aes(x = aec_r_2030_baseline_lab_cc_avg, color = 'Direct CC')) +
  stat_ecdf(data = ca_microsim_cc,
            aes(x = aec_r_2030_baseline, color = 'Baseline')) +
  labs(
    color = "Scenario Variant",
    # title = "Comparison of Cumulative Consumption Distributions",
    x = "Equivalized consumption (Dram)",
    y = "Cumulative Probability") +
  theme_minimal() +
  coord_cartesian(xlim = c(40000, 110000)) +
  scale_x_continuous(labels = scales::comma) +
  # geom_vline(xintercept = 55883,
  #            color = "red",
  #            linetype = "dotted",
  #            linewidth = 0.8) +
  # annotate("text",
  #          x = 55883,
  #          y = 0.5,
  #          label = "Poverty line",
  #          color = "black",
  #          hjust = -0.1,
  #          size = 3) +
  annotate("segment", x = 70000, xend = 65000, y = 0.2, yend = 0.2,
           arrow = arrow(length = unit(0.3, "cm")), color = "black") +
  annotate("text", x = 72500, y = 0.2, label = "Shift due to shocks", hjust = 0)
```



```
  # annotate("segment", x = 80000, xend = 75000, y = 0.4, yend = 0.4,
  #          arrow = arrow(length = unit(0.3, "cm")), color = "black") +
  # annotate("text", x = 82500, y = 0.4, label = "Shift due to shocks", hjust = 0)
```

For energy prices

```
# Plot the cumulative distribution with left-facing arrows
ggplot(ca_microsim_cc,
       aes(x = aec_r_2030_EM_nzs_energy, color = 'NZS + Energy Price')) +
  stat_ecdf(geom = "step") +
  # stat_ecdf(data = ca_microsim_cc,
  #           aes(x = aec_r_2030_baseline_lab_avg, color = 'Baseline + Labor Productivity'))
  stat_ecdf(data = ca_microsim_cc,
            aes(x = aec_r_2030_EM_baseline_energy, color = 'Baseline + Energy Price')) +
  stat_ecdf(data = ca_microsim_cc,
            aes(x = aec_r_2030_baseline, color = 'Baseline')) +
  labs(
    color = "Scenario Variant",
    # title = "Comparison of Cumulative Consumption Distributions",
    x = "Equivalized consumption (Dram)",
    y = "Cumulative Probability") +
  theme_minimal() +
  coord_cartesian(xlim = c(40000, 110000)) +
  scale_x_continuous(labels = scales::comma) +
  # geom_vline(xintercept = 55883,
  #            color = "red",
  #            linetype = "dotted",
  #            linewidth = 0.8) +
  # annotate("text",
  #          x = 55883,
  #          y = 0.5,
  #          label = "Poverty line",
  #          color = "black",
  #          hjust = -0.1,
  #          size = 3) +
  annotate("segment", x = 70000, xend = 65000, y = 0.2, yend = 0.2,
           arrow = arrow(length = unit(0.3, "cm")), color = "black") +
  annotate("text", x = 72500, y = 0.2, label = "Shift due to shocks", hjust = 0)
```



```
  # annotate("segment", x = 80000, xend = 75000, y = 0.4, yend = 0.4,
  #          arrow = arrow(length = unit(0.3, "cm")), color = "black") +
  # annotate("text", x = 82500, y = 0.4, label = "Shift due to shocks", hjust = 0)
```

0.8.5 Disaggregation of poverty measures

We bring back poverty to the people's dataset.

```
# We extract household poverty designations from the data
new_poor <- ca_microsim_cc %>%
  select(hhid,
         weight_2030_baseline,
         weight_2030_dry_hot,
         poor_Avpovln2022_2022,
         poor_Avpovln2022_2030_baseline,
         poor_Avpovln2022_2030_dry_hot,
         poor_Avpovln2022_2030_nzs,
         poor_2030_baseline_lab_avg,
         poor_2030_baseline_lab_max,
         poor_2030_baseline_cc_avg,
         poor_2030_baseline_cc_max,
         poor_2030_baseline_lab_cc_avg,
         poor_2030_baseline_lab_cc_max,
         poor_2030_baseline_food1,
         poor_2030_dry_hot_food2,
         poor_2030_baseline_lab_cc_foodPI,
         poor_2030_baseline_energy,
         poor_2030_nzs_energy,
         poor_2030_EM_baseline_energy,
         poor_2030_EM_nzs_energy
         )

# And merge them back into the people dataset
pp_microsim_cc <- pp_microsim_cc %>%
  select(-c(poor_Avpovln2022,
           weight_2030_baseline,
           weight_2030_dry_hot)) %>%
  left_join(new_poor, join_by(hhid)) %>%
  mutate(female = if_else(gender == 2, 1,0),
         youth = if_else(age < 15, 1, 0))
```

Let's find homes where more than 50% of income comes from agriculture. We first find the fraction of household labor income that comes from agriculture.

```
ag_labinc_fraction <- pp_microsim_cc %>%
  mutate(
    ag_lab_income =
      if_else(
        lmarket == 1,
        monthly_labor_income_2030_baseline, NA)
  ) %>%
  group_by(hhid) %>%
  summarize(
    ag_labinc =
      sum(ag_lab_income, na.rm = TRUE),
    hh_labinc =
      sum(monthly_labor_income_2030_baseline, na.rm = TRUE)) %>%
  mutate(ag_lab_fraction = if_else(hh_labinc == 0, 0, ag_labinc/ hh_labinc)) %>%
  select(hhid, ag_lab_fraction)
```

And then we add ag income sources and evaluate if they are at least 50% of total income

```r
ag_income_50 <- ic_microsim_cc %>%
  left_join(ag_labinc_fraction, join_by(interview__key==hhid)) %>%
  rename(hhid = interview__key) %>%
  mutate(
    across(
      c(inc2_2030_baseline,
        inc3_2030_baseline,
        inc4,
        totalinc_2030_baseline), ~replace_na(., 0))) %>%
  mutate(
    ag_income =
      inc2_2030_baseline +
      inc3_2030_baseline +
      inc4 * ag_lab_fraction,
    ag_fraction = if_else(
      totalinc_2030_baseline == 0, 0, ag_income / totalinc_2030_baseline)
    ) %>%
  mutate(
    is_ag_home = if_else(ag_fraction >= 0.5, "Ag. HH (>= 50%)", "Other HH")
  ) %>%
  select(hhid, is_ag_home)
```

We make a table to see who became poor.

0.8.6 The table

```r
test <- pp_microsim_cc

test <- test%>%
  left_join(ag_income_50, join_by(hhid)) %>%
#   filter(rural ==1 & is_ag_home == "Ag. HH (>= 50%)") %>%
  rename(poor_original = poor_Avpovln2022_2030_baseline,
         poor_dh = poor_Avpovln2022_2030_dry_hot,
         poor_nzs = poor_Avpovln2022_2030_nzs,
         poor_lab = poor_2030_baseline_lab_avg,
         poor_cc = poor_2030_baseline_cc_avg,
         poor_lab_cc = poor_2030_baseline_lab_cc_avg,
         poor_foodPI = poor_2030_baseline_lab_cc_foodPI,
         poor_dh_food = poor_2030_dry_hot_food2,
         poor_b_energy = poor_2030_baseline_energy,
         poor_nzs_energy = poor_2030_nzs_energy,
         poor_EM_b_energy = poor_2030_EM_baseline_energy,
         poor_EM_nzs_energy = poor_2030_EM_nzs_energy
         ) %>%
  group_by(poor_nzs, poor_EM_nzs_energy) %>%
  summarize(no_pp = sum(weight_2030_nzs, na.rm = TRUE),
            female = sum(female*weight_2030_nzs, na.rm = TRUE),
            male = no_pp - female,
            youth = sum(youth*weight_2030_nzs, na.rm = TRUE),
            non_youth = no_pp - youth,
            rural = sum(rural *weight_2030_nzs, na.rm = TRUE),
            urban = no_pp - rural
            )
```

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

```
test %>%
  gt()
```

poor_EM_nzs_energy	no_pp	female	male	youth	non_youth	rural
0						
0	2376884.720	1304727.583	1072157.137	450102.388	1926782.332	906106.986
1	4549.283	2583.922	1965.362	1088.172	3461.112	3929.787
1						
1	451593.951	246849.815	204744.136	120979.071	330614.880	214857.559

```
write.table(test, "clipboard", sep="\t", row.names=FALSE)
```

```
# foodpoor <- ca_microsim_cc %>%
#   mutate(new_poor_food_base = if_else(
#     poor_2030_baseline_lab_cc_foodPI == 1 &
#       poor_2030_baseline_lab_cc_avg == 0, 1, 0),
#          new_poor_food_dryhot = if_else(
#            poor_cc_avg_food1 == 1 & poor_cc_avg == 0, 1, 0),
#     NAM_1 = as_factor(marz)) %>%
#   mutate(NAM_1 = if_else(NAM_1 == "VayotsDzor", "Vayots Dzor", NAM_1)) %>%
#   mutate(NAM_1 = if_else(NAM_1 == "Sjunik", "Syunik", NAM_1)) %>%
#   select(NAM_1, poor_Avpovln2022_2022,
#          poor_Avpovln2022_2030_baseline,
#          poor_Avpovln2022_2030_dry_hot,
#          poor_2030_baseline_lab_avg,
#          poor_2030_baseline_lab_max,
#          poor_2030_baseline_cc_avg,
#          poor_2030_baseline_cc_max,
#          poor_2030_baseline_lab_cc_avg,
#          poor_2030_baseline_lab_cc_max,
#          poor_2030_baseline_food1,
#          poor_2030_dry_hot_food2,
#          poor_2030_baseline_lab_cc_foodPI,
#          weight_2030_baseline,
#          weight_2030_dry_hot,
#          hhsize)
#
# fp <-foodpoor %>%
#   group_by(NAM_1) %>%
#   summarize(new_poor = round(sum(new_poor_food_dryhot * weight*hhsize, na.rm = TRUE))) %>%
#   mutate(label = paste0(NAM_1," (", new_poor, ")"))
#
#
# ##write.table(fp, "clipboard", sep="\t", row.names=FALSE)
# fp_map <- adm1 |>
#   left_join(fp, join_by(NAM_1 == NAM_1))
#
# fp_map <-tm_shape(fp_map)+
#   tm_polygons("new_poor", legend.show = FALSE) +
#   tm_text("label", size = .7, col = "black")+
#   tm_layout(legend.position = c("right", "top"),
#             title= "Additional Poor Dry-Hot Scenario",
#             title.position = c('left', 'bottom'),
#             title.size = 0.9)
#
# fp_map
```

```
new_poor_scenarios <- pp_microsim_cc %>%
  left_join(ag_income_50, join_by(hhid)) %>%
  mutate(
    poor_baseline = poor_Avpovln2022_2030_baseline,
    poor_dry_hot = poor_Avpovln2022_2030_dry_hot,
    poor_nzs = poor_Avpovln2022_2030_nzs,
    new_poor_lab_cc = if_else(
      poor_Avpovln2022_2030_baseline == 0 &
        poor_2030_baseline_lab_cc_avg == 1,
      1,
      0
    ),
    new_poor_lab_cc_foodPI = if_else(
      poor_Avpovln2022_2030_baseline == 0 &
        poor_2030_baseline_lab_cc_foodPI == 1,
      1,
      0
    ),
    new_poor_dry_hot_food2 = if_else(
      poor_Avpovln2022_2030_dry_hot == 0 &
        poor_2030_dry_hot_food2 == 1,
      1,
      0
    ),
    new_poor_b_energy = if_else(
      poor_Avpovln2022_2030_baseline == 0 &
        poor_2030_baseline_energy == 1,
      1,
      0
    ),
    new_poor_nzs_energy = if_else(
      poor_Avpovln2022_2030_nzs == 0 &
        poor_2030_nzs_energy == 1,
      1,
      0
    ),
    new_poor_EM_b_energy = if_else(
      poor_Avpovln2022_2030_baseline == 0 &
        poor_2030_EM_baseline_energy == 1,
      1,
      0
    ),
    new_poor_EM_nzs_energy = if_else(
      poor_Avpovln2022_2030_nzs == 0 &
        poor_2030_EM_nzs_energy == 1,
      1,
      0
    )
```

```
  ) %>%
  group_by(NAM_1) %>% # has to be NAM_1 for the next chunk to work
  summarize(
    total_population = sum(weight_2030_baseline, na.rm = TRUE),
    poor_baseline =
      sum(poor_baseline * weight_2030_baseline, na.rm = TRUE),
    poor_dry_hot =
      sum(poor_dry_hot * weight_2030_dry_hot, na.rm = TRUE),
    poor_nzs =
      sum(poor_nzs * weight_2030_nzs, na.rm = TRUE),
    new_p_lab_cc =
      sum(new_poor_lab_cc * weight_2030_baseline, na.rm = TRUE),
    new_p_lab_cc_foodPI =
      sum(new_poor_lab_cc_foodPI * weight_2030_baseline, na.rm = TRUE),
    new_p_dry_hot_food2 =
      sum(new_poor_dry_hot_food2 * weight_2030_dry_hot, na.rm = TRUE),
    new_p_baseline_energy =
      sum(new_poor_b_energy * weight_2030_baseline, na.rm = TRUE),
    new_p_nzs_energy =
      sum(new_poor_nzs_energy * weight_2030_nzs, na.rm = TRUE),
    new_p_EM_baseline_energy =
      sum(new_poor_EM_b_energy * weight_2030_baseline, na.rm = TRUE),
    new_p_EM_nzs_energy =
      sum(new_poor_EM_nzs_energy * weight_2030_nzs, na.rm = TRUE)
  )

write.table(new_poor_scenarios, "clipboard", sep="\t", row.names=FALSE)

##write.table(test, "clipboard", sep="\t", row.names=FALSE)
```

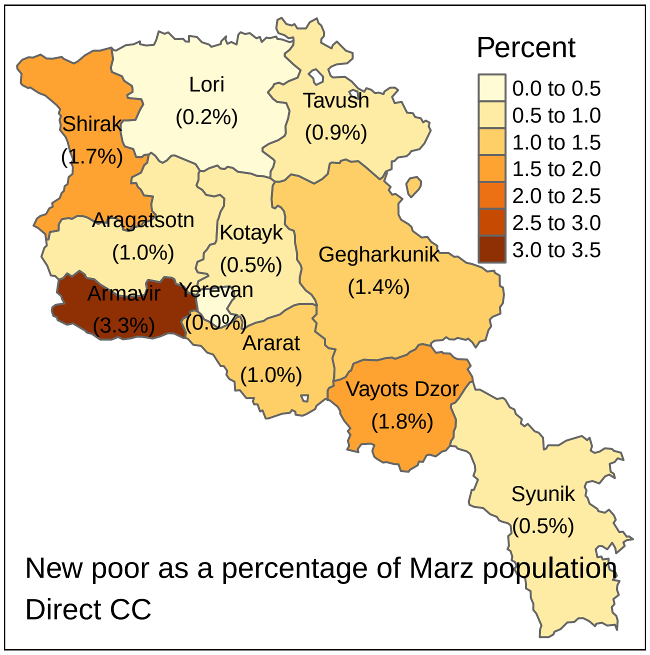
And we create labels for our map.

```
new_poor_map <- adm1 %>% # previous chunk has to be grouped by NAM_1
  left_join(new_poor_scenarios, join_by(NAM_1)) %>%
  mutate(
    new_p_lab_cc_pct = new_p_lab_cc / total_population *
          100,
    new_poor_lab_cc_foodPI_pct = new_p_lab_cc_foodPI /
         total_population * 100,
    new_poor_dry_hot_food2_pct = new_p_dry_hot_food2 /
         total_population * 100,
    new_poor_baseline_energy_pct = new_p_baseline_energy /
```

```
      total_population*100,
    new_poor_nzs_energy_pct = new_p_nzs_energy / total_population * 100,
    new_poor_EM_baseline_energy_pct = new_p_EM_baseline_energy /
      total_population*100,
    new_poor_EM_nzs_energy_pct = new_p_EM_nzs_energy / total_population * 100
  ) %>%
  mutate(
    new_p_lab_cc_label    = paste0(NAM_1, "\n(", sprintf("%.1f%%", new_p_lab_cc_pct), ")"),
    new_p_lab_cc_foodPI_label = paste0(NAM_1, "\n(", sprintf("%.1f%%", new_poor_lab_cc_foodPI
    new_p_dry_hot_food2_label = paste0(NAM_1, "\n(", sprintf("%.1f%%", new_poor_dry_hot_food2
    new_p_b_energy_label = paste0(NAM_1, "\n(", sprintf("%.1f%%", new_poor_baseline_energy_pc
    new_p_nzs_energy_label = paste0(NAM_1, "\n(", sprintf("%.1f%%", new_poor_nzs_energy_pct)
    new_p_EM_b_energy_label = paste0(NAM_1, "\n(", sprintf("%.1f%%", new_poor_EM_baseline_ene
    new_p_EM_nzs_energy_label = paste0(NAM_1, "\n(", sprintf("%.1f%%", new_poor_EM_nzs_energy
  )
```

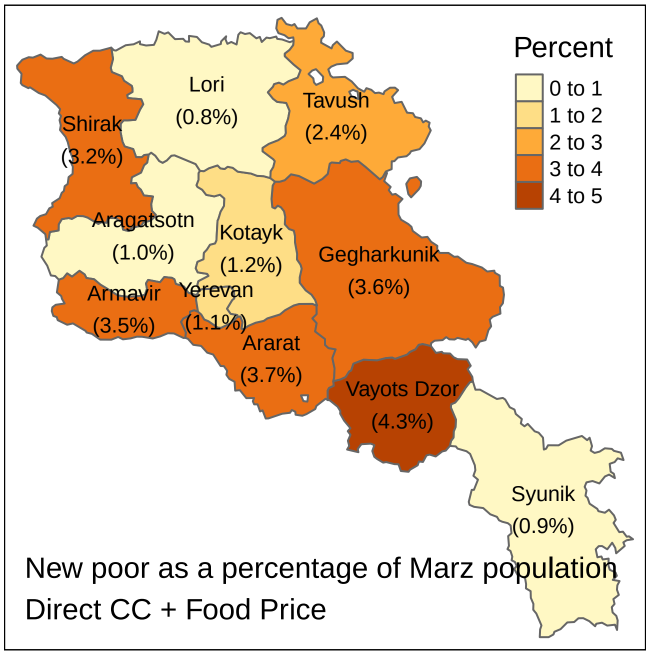
Let’s map different scenarios.

```
tm_shape(new_poor_map)+
  tm_polygons("new_p_lab_cc_pct", title="Percent", legend.show = TRUE) +
  tm_text(c("new_p_lab_cc_label"), size = .7, col = "black")+
  tm_layout(legend.position = c("right", "top"),
            #legend.outside = TRUE,
            title= "New poor as a percentage of Marz population\nDirect CC",
            title.position = c('left', 'bottom'),
            title.size = 0.9)
```



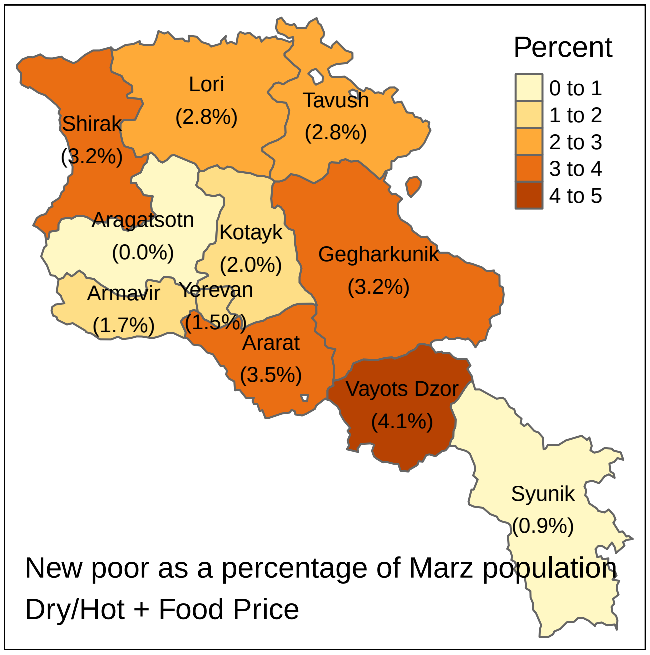
And the second variant

```
tm_shape(new_poor_map)+
  tm_polygons("new_poor_lab_cc_foodPI_pct",
              title="Percent",
              legend.show = TRUE) +
  tm_text(c("new_p_lab_cc_foodPI_label"), size = .7, col = "black")+
  tm_layout(legend.position = c("right", "top"),
            title= "New poor as a percentage of Marz population\nDirect CC + Food Price",
#            outer.margins=c(.10,.10, .10, .10),
            title.position = c('left', 'bottom'),
            title.size = 0.9)
```



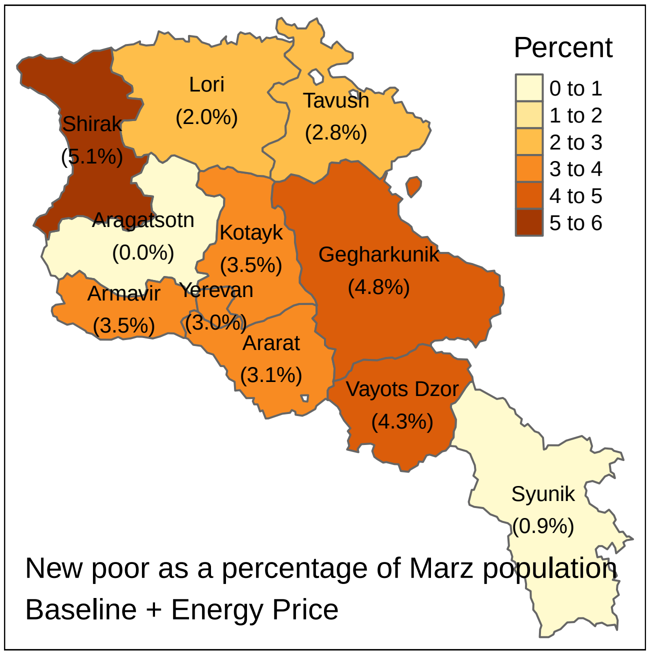
Second variant b

```
tm_shape(new_poor_map)+
  tm_polygons("new_poor_dry_hot_food2_pct",
              title="Percent",
              legend.show = TRUE) +
  tm_text(c("new_p_dry_hot_food2_label"), size = .7, col = "black")+
  tm_layout(legend.position = c("right", "top"),
            title= "New poor as a percentage of Marz population\nDry/Hot + Food Price",
#            outer.margins=c(.10,.10, .10, .10),
            title.position = c('left', 'bottom'),
            title.size = 0.9)
```



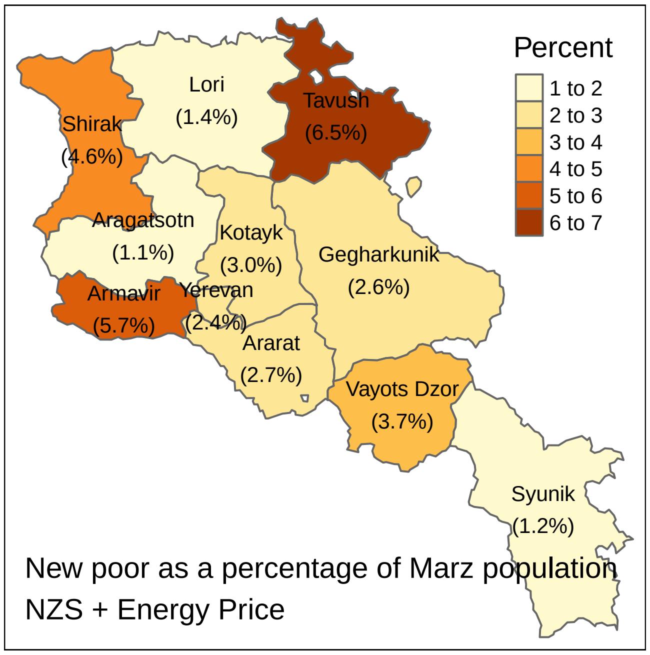
And the third variant

```
tm_shape(new_poor_map)+
  tm_polygons("new_poor_baseline_energy_pct",
              title="Percent",
              legend.show = TRUE) +
  tm_text(c("new_p_b_energy_label"), size = .7, col = "black")+
  tm_layout(legend.position = c("right", "top"),
            title= "New poor as a percentage of Marz population\nBaseline + Energy Price",
#            outer.margins=c(.10,.10, .10, .10),
            title.position = c('left', 'bottom'),
            title.size = 0.9)
```



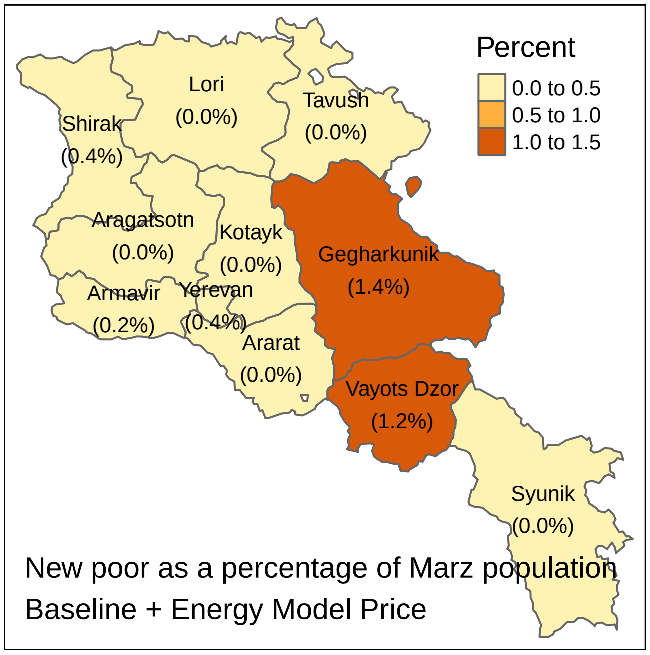
And the fourth variant

```
tm_shape(new_poor_map)+
  tm_polygons("new_poor_nzs_energy_pct",
              title="Percent",
              legend.show = TRUE) +
  tm_text(c("new_p_nzs_energy_label"), size = .7, col = "black")+
  tm_layout(legend.position = c("right", "top"),
            title= "New poor as a percentage of Marz population\nNZS + Energy Price",
#            outer.margins=c(.10,.10, .10, .10),
            title.position = c('left', 'bottom'),
            title.size = 0.9)
```



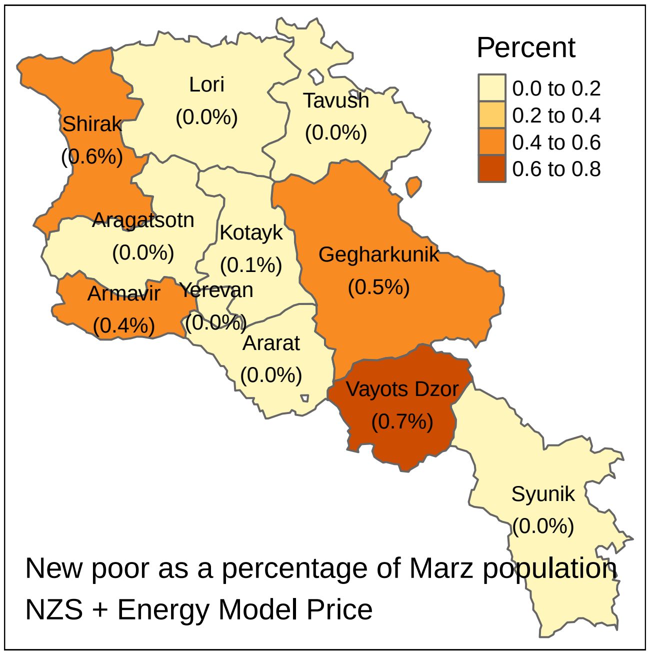
Fifth

```
tm_shape(new_poor_map)+
  tm_polygons("new_poor_EM_baseline_energy_pct",
              title="Percent",
              legend.show = TRUE) +
  tm_text(c("new_p_EM_b_energy_label"), size = .7, col = "black")+
  tm_layout(legend.position = c("right", "top"),
            title= "New poor as a percentage of Marz population\nBaseline + Energy Model Pri
#            outer.margins=c(.10,.10, .10, .10),
            title.position = c('left', 'bottom'),
            title.size = 0.9)
```



Sixth

```
tm_shape(new_poor_map)+
  tm_polygons("new_poor_EM_nzs_energy_pct",
              title="Percent",
              legend.show = TRUE) +
  tm_text(c("new_p_EM_nzs_energy_label"), size = .7, col = "black")+
  tm_layout(legend.position = c("right", "top"),
            title= "New poor as a percentage of Marz population\nNZS + Energy Model Price",
#            outer.margins=c(.10,.10, .10, .10),
            title.position = c('left', 'bottom'),
            title.size = 0.9)
```



Now let's show average losses by decile as a percentage of total spending.

```
avg_scenario_losses <- ca_microsim_cc %>%
  mutate(
    totc_loss_lab_cc = if_else(
      (totc_2030_baseline_lab_cc_avg - totc_2030_baseline)< 0,
      (totc_2030_baseline_lab_cc_avg - totc_2030_baseline)/
        totc_2030_baseline,NA),
    totc_loss_lab_cc_foodPI = if_else(
      (totc_2030_baseline_lab_cc_foodPI - totc_2030_baseline)< 0,
      (totc_2030_baseline_lab_cc_foodPI - totc_2030_baseline)/
        totc_2030_baseline,NA)
         ) %>%
  group_by(decile) %>%
  summarize(no_hh =
              round(
                sum(
                  weight_2030_baseline, na.rm = TRUE), digits = 0
                ),
            avg_totc =
              round(
                weighted.mean(
                  totc_2030_baseline, weight_2030_baseline, na.rm = TRUE), digits = 2
                ),
            avg_totc_usd =
              round(
                weighted.mean(
                  totc_2030_baseline, weight_2030_baseline, na.rm = TRUE)*er, digits = 1
                ),
            avg_loss_lab_cc =
              round(
                weighted.mean(
                  totc_loss_lab_cc,
                  weight_2030_baseline,
                  na.rm = TRUE),
                digits = 4
                ),
            avg_loss_lab_cc_foodPI =
              round(
                weighted.mean(
                  totc_loss_lab_cc_foodPI,
                  weight_2030_baseline,
                  na.rm = TRUE), digits = 4),
            # avg_loss_b_energy =
            #   round(
            #     weighted.mean(
            #       totc_loss_lab_cc_foodPI,
            #       weight_2030_baseline,
            #       na.rm = TRUE), digits = 4),
            # avg_loss_nzs_energy =
            #   round(
            #     weighted.mean(
            #       totc_loss_lab_cc_foodPI,
            #       weight_2030_baseline,
            #       na.rm = TRUE), digits = 4),
            # avg_loss_EM_b_energy =
            #   round(
            #     weighted.mean(
            #       totc_loss_lab_cc_foodPI,
            #       weight_2030_baseline,
            #       na.rm = TRUE), digits = 4),
            # avg_loss_EM_nzs_energy =
            #   round(
            #     weighted.mean(
            #       totc_loss_lab_cc_foodPI,
            #       weight_2030_baseline,
            #       na.rm = TRUE), digits = 4)
            )

##write.table(avg_scenario_losses, "clipboard", sep="\t", row.names=FALSE)

avg_scenario_losses %>%
  gt()
```

Decile of aec_r, with pweight	no_hh	avg_totc	avg_totc_usd	avg_loss_lab_cc	avg_loss_lab_cc_f
1	54366	150233.1	347.0	-0.0088	-0
2	59969	173070.4	399.8	-0.0109	-0
3	61790	197378.1	455.9	-0.0100	-0
4	66999	208086.4	480.7	-0.0091	-0
5	73341	210340.4	485.9	-0.0110	-0
6	80796	213555.7	493.3	-0.0113	-0
7	80304	236754.2	546.9	-0.0097	-0
8	88195	244050.4	563.8	-0.0119	-0
9	96945	254350.8	587.6	-0.0090	-0
10	120886	310809.4	718.0	-0.0105	-0

Energy price index interpolation

```
# Sample data
data <- data.frame(
  year = c(2020, 2030),
  value = c(100.00000,103.18920)
)

# Define the years for interpolation
years <- seq(2020, 2030, by = 1)

# Perform linear interpolation
interpolated_values <- approx(data$year, data$value, xout = years)

# Create a data frame with the interpolated results
interpolated_data <- data.frame(
  year = interpolated_values$x,
  value = interpolated_values$y
)
```

```
# Display the result
print(interpolated_data)
```

```
   year    value
1  2020 100.0000
2  2021 100.3189
3  2022 100.6378
4  2023 100.9568
5  2024 101.2757
6  2025 101.5946
7  2026 101.9135
8  2027 102.2324
9  2028 102.5514
10 2029 102.8703
11 2030 103.1892
```

The inquiry is who is getting hit the most from changes to energy prices.

```
energy_shares <- ca_microsim_cc %>%
  left_join(ag_income_50, join_by(hhid)) %>%
  mutate(
    shr_energy = if_else(totc_2022==0,NA, (hous_23+hous_36_b+hous_29_b)/totc_2022)
  ) %>%
  group_by(decile, is_ag_home) %>%
  summarize(no_hh= sum(weight_2022, na.rm = TRUE),
            shr_e = weighted.mean(shr_energy, weight_2022, na.rm=TRUE))
```

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

```
write.table(energy_shares, "clipboard", sep="\t", row.names=FALSE)
```

End

ARMSTAT. (2023). *Integrated Living Conditions Survey 2022*.
Strzepek, K., Boehlert, B., Castillo, D., & Smet, K. (2024). *Estimating the Economic Impacts of Climate Change in Armenia*. Industrial Economics, Incorporated / The World Bank.

Listing 6 Annualized labor income

```
pp_microsim <- pp_microsim %>%
  # Labor income primary job
  mutate(annual_labor_income_primary = case_when(
    emp_12 == 1 ~ emp_11 * 365,
    emp_12 == 2 ~ (emp_11/7) * 365,  # Assuming weekly rate
    emp_12 == 3 ~ (emp_11/14) * 365,
    emp_12 == 4 ~ emp_11 * 12,
    emp_12 == 5 ~ emp_11 * 2,
    emp_12 == 6 ~ emp_11,
    emp_12 == 7 ~ NA
  ))   %>%
  # Labor income secondary job
  mutate(annual_labor_income_secondary = case_when(
    emp_26 == 1 ~ emp_25 * 365,
    emp_26 == 2 ~ (emp_25/7) * 365,  # Assuming weekly rate
    emp_26 == 3 ~ (emp_25/14) * 365,
    emp_26 == 4 ~ emp_25 * 12,
    emp_26 == 5 ~ emp_25 * 2,
    emp_26 == 6 ~ emp_25,
    emp_26 == 7 ~ NA
  )) %>%
  # Annual labor total in thousands of dram
  mutate(annual_labor_total =
           (coalesce(annual_labor_income_primary, 0) +
           coalesce(annual_labor_income_secondary, 0))/1000)

# Restore annual_labor_total to NA if both NA
pp_microsim <- pp_microsim %>%
  mutate(annual_labor_total =
           if_else(
             is.na(annual_labor_income_primary)
             & is.na(annual_labor_income_secondary),
         NA,
         annual_labor_total))
```

Listing 7 Employed with no income reported

```
total_employed_no_income <- pp_microsim %>%
  filter(employed == TRUE & is.na(annual_labor_total)) %>%
  nrow()

total_employed <- pp_microsim %>%
  filter(employed == TRUE) %>%
  nrow()

percent_employed_no_income <-
  (total_employed_no_income / total_employed) * 100

print(
  paste0(
    "There is ",
    format(
      percent_employed_no_income,digits = 2, nsmall=2
      ),
    "% of the employed population that reports no income.")
  )
```

Listing 8 Sector aggregation

```
pp_microsim <- pp_microsim %>%
  mutate(emp_04 = as.integer(emp_04)) %>%
  left_join(sectors, join_by("emp_04" == "economic_activity_code") ) %>%
  rename(sector = ea_shortcode)
```

Listing 9 Assign sector to those who don't report one

```
pp_microsim <- pp_microsim %>%
  group_by(hhid) %>%
  mutate(
    # Create a temporary variable 'other_sector'
    # which captures the sector of any employed
    # individual in the household
    other_sector =
      if_else(employed == TRUE & !is.na(sector), sector, NA_real_)
  ) %>%
  # Use 'fill' to propagate 'other_sector' values within the household
  fill(other_sector, .direction = "downup") %>%
  mutate(
    # Impute missing 'sector' values based on the 'other_sector'
    sector =
      if_else(is.na(sector) & employed == TRUE, other_sector, sector)
  ) %>%
  # Drop the temporary 'other_sector' variable
  select(-other_sector) %>%
  ungroup()
```

Listing 10 No sector for OLF

```
pp_microsim <- pp_microsim %>%
  mutate(lstatus = as.numeric(lstatus),
         sector =
           if_else(lstatus == 4,
                   as.character(NA),
                   as.character(sector)),
         industry = as.factor(sector)) %>%
  # We need this for reweighting and
  # not messing up the regression below.
  mutate(sector_w = sector)
```

Listing 11 Income regression model

```
model <- lm(lnlab ~ age + gender + educy + age2 + marz + sector,
            data = regression_data)
```