# IPUMS Training and Development: Requesting Data

IPUMS PMA Exercise 2

OBJECTIVE: Gain an understanding of how IPUMS PMA service delivery point datasets are structured and how it can be leveraged to explore your research interests.

10/24/2018

## Objectives

- Create and download an IPUMS PMA data extract
- Decompress data file and read data in R
- Analyze the data using sample code
- Validate data analysis work using answer key

## IPUMS Variables

- EAID: Enumeration area (primary sampling unit)
- FACILITYTYPEGEN: Type of facility
- FACILITYADV: Advanced facility
- PILLOBS: Observed and in or out of stock of birth control pills
- PILLOUTDAY: Number of days birth control pills have been out of stock
- URBAN: Urban or rural status

## R Code to Review

This tutorial's sample code and answers use the so-called "tidyverse" style, but R has the blessing (and curse) that there are many different ways to do almost everything. If you prefer another programming style, please feel free to use it. But, for your reference, these are some quick explanations for commands that this tutorial will use:

- **%>%** - The pipe operator which helps make code with nested function calls easier to read. When reading code, it can be read as "and then". The pipe makes it so that code like ingredients %>% stir() %>% cook() is equivalent to cook(stir(ingredients)) (read as "take ingredients and then stir and then cook").
- **as_factor** - Converts the value labels provide for IPUMS data into a factor variable for R
- **summarize** - Summarize a datasets observations to one or more groups
- **group_by** - Set the groups for the summarize function to group by
- **filter** - Filter the dataset so that it only contains these values
- **mutate** - Add on a new variable to a dataset
- **weighted.mean** - Get the weighted mean of the a variable
- **count** - Frequency count for a variable or value
- **ggplot** - Initializes a graphic object (histogram, box plot, etc.)

## Review Answer Key (page 10)

## Common Mistakes to Avoid

1. Not changing the working directory to the folder where your data is stored
2. Mixing up = and ==; To assign a value in generating a variable, use "<-" (or "="). Use "==" as a logical test for equality between two objects.

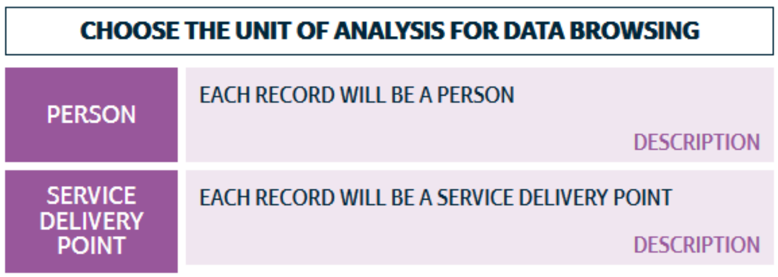
Step 1

Make an Extract

## Registering with IPUMS

Go to http://pma.ipums.org, click on Register to Use IPUMS PMA on the left hand side of the screen. Click the Register for IPUMS PMA button and fill out the form to apply for access. You will have to wait for your account to be approved to access the data. Once you receive the approval email, click "Log In" at the top of the page and use your email and password.

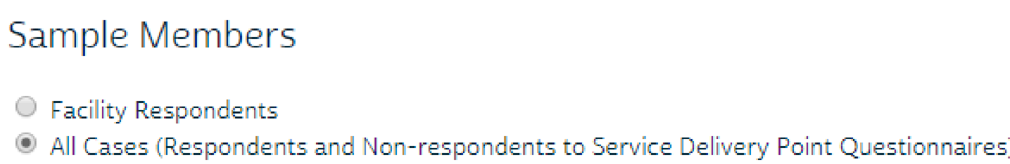
- Go to Select Data
- Choose the Service Delivery Point unit of analysis




- Click the Select Samples box, check the box for the Kenya 2016 R5


- Scroll to the bottom of the page and click the radio button option for All Cases. The default is Facility Respondents

- Click the Submit Sample Selections box



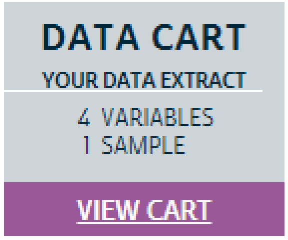

- Using the drop down menu or search feature, select the following variables:

FACILITYTYPEGEN: Type of facility
FACILITYADV: Advanced facility
PILLOBS: In or out of stock of birth control pills
PILLOUTDAY: Number of days birth control pills have been out of stock
URBAN: Urban or rural status

**Step 2**

**Request the Data**

- Click the purple VIEW CART button under your data cart




- Review variable selection. Note that certain variables appear in your data cart even if you did not select them, and they are not included in the constantly updated count of variables in your data cart. The preselected variables are needed for weighting, for variance estimation, or to identify the year, country, and round of a sample.
- Click the Create Data Extract button
- Review the 'Extract Request Summary' screen, describe your extract and click Submit Extract
- You will get an email when the data is available to download.
- To get to the page to download the data, follow the link in the email, or follow the My Data Extracts link on the homepage.

**Step 3**

**Open the file in R**

## Getting the data into your statistics software

### Download the data

- Go to http://pma.ipums.org and click on My Data Extracts

| Extract Number | Date | Formatted Data | Fixed-width Text Files | | | | | | Codebook | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | Data | Command Files | | | | | | |
| 36 | 2018-10-15 | Download STATA | -- | - | - | - | - | | Basic | DDI |

- Right-click on the data link next to extract you created
- Choose "Save Target As..." (or "Save Link As...")
- Save into "Documents" (that should pop up as the default location)
- Do the same thing for the DDI link next to the extract
- (Optional) Do the same thing for the R script
- You do not need to decompress the data to use it in R

### Install and load packages for R

- Open R from the Start menu
- If you haven't already installed any of the following packages, type:

```
install.packages("ipumsr")
install.packages("dplyr")
install.packages("ggplot2")
```

- Next (or if you have already installed the packages on your computer), type:

```
library(ipumsr)
```

library(dplyr)

library(ggplot2)

options(tibble.print_max = Inf)

Read data into R

- Set your working directory to where you saved the data above by adapting the following command (Rstudio users can also use the "Project" feature to set the working directory. In the menubar, select File -> New Project -> Existing Directory and then navigate to the folder):

setwd("~/") # "~/" goes to your Documents directory on most computers

- Run the following command from the console, adapting it so it refers to the extract you just created (replace the #s below with the number of your extract):

ddi <- read_ipums_ddi("pma_000##.xml")

SDP <- read_ipums_micro(ddi)

- This exercise demonstrates how to merge SDP data to the HHF dataset used in Exercise 1. **Please see instructions in Exercise 1 to ensure that your HHF extract contains the variables used below.** Load the HHF data using the following commands (your HHF extract will have different #s than the SDP extract):

ddi <- read_ipums_ddi("pma_000##.xml")

HHF <- read_ipums_micro(ddi)

- NOTE: To stay consistent with the exercises for other statistical packages, this exercise does not spend much time on the helpers to allow for translation of the way IPUMS uses labelled values to the way base R does. you can learn more about these in the value-labels vignette in the R package. From R run command: vignette("value-labels", package = "ipumsr")

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Section 1

Explore the Data

## Analyze the sample - Part 1: Exploring Facility Types

**A**) Create a frequency table for FACILITYTYPEGEN showing the proportion of each type of facility surveyed in Kenya 2016 Round 5.

______________________________

```
SDP %>%
  count(type <- as_factor(FACILITYTYPEGEN)) %>%
  mutate(prop = prop.table(n))
```

Section 1

Explore the Data

**B**) According to the Universe tab, what facilities are included in the surveyed universe for FACILITYTYPEGEN?
__________________________

**C**) Users should note that many variables in the service delivery point (SDP) survey have a universe defined by FACILITYADV, a country-specific designation of "advanced facility" types. Create a crosstab to see which types of facilities from the previous question were designated as "advanced facilities" in Kenya for 2016.
__________________________

```
SDP %>%
  mutate(ADVANCED = FACILITYADV==1)%>%
  group_by(as_factor(FACILITYTYPEGEN), ADVANCED)%>%
  summarize()
```

**D**) Consult the Comparability tab for FACILITYADV, taking care to note that advanced facility designations vary by country, and sometimes vary by survey round within a country. Locate the entry for Kenya, and determine whether its advanced facility designation matches what you found in Question C. Is the designation consistent for all Kenyan survey rounds that included this variable? _______________

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Section 2

Analyze the Data

**Analyze the sample - Part 2: Descriptive Statistics**

**A**) Consider the variable PILLOBS, which describes whether the SDP had an observable stock of birth control pills on the day of the interview. According to the Codes tab, what are the possible responses for SDPs surveyed in Kenya 2016?__________________

**B**) According to the Comparability tab, possible responses to PILLOBS may vary from sample to sample. How so? ___________________

**C**) According to the Universe tab, what facilities are included in the surveyed universe for PILLOBS?
_________________________________________________

**D**) Among facilities that usually provide birth control pills shown in PILLOBS, what type of facility was least likely to have supplies of birth

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Analyze the Data

control pills in-stock on the day of the interview? What proportion of facilities of this type were out of stock? (Restrict analysis only to completed interviews and in-universe cases). ________________________________________

```
SDP%>%
  filter(PILLOBS < 90)%>%
  count(FACILITYTYPEGEN, PILLOBS)%>%
  group_by(FACILITYTYPEGEN)%>%
  mutate(type = as_factor(FACILITYTYPEGEN))%>%
  mutate(obs = as_factor(PILLOBS))%>%
  mutate(prop_type = prop.table(n))%>%
  select(type, obs, n, prop_type)
```

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Section 3

Visualize the Data

**Analyze the sample - Part 3: Data Visualization**

**A)** For facilities that were out of birth control pills, PILLOUTDAY shows the number of days that supplies had been unavailable. Because some SDPs had been out of stock for more than 90 days, NIU and missing value codes for PILLOUTDAY are coded as values 9994, 9997, and 9999 in order to exceed the range of valid responses.

Calculate the mean shortage of pills for *all* in-universe facilities in PILLOUTDAY, taking care to exclude any value above 9000. Then find the mean for *each facility type* in FACILITYTYPEGEN, and display the result as a bar chart. (Restrict analysis only to valid responses from SDPs in universe for PILLOUTDAY). ______________________________

Section 3

Visualize the Data

```
SDP%>%
  filter(PILLOUTDAY < 9000)%>%
  summarise(mean(PILLOUTDAY))
SDP%>%
  filter(PILLOUTDAY < 9000)%>%
  group_by(as_factor(FACILITYTYPEGEN))%>%
  summarise(mean(PILLOUTDAY))
SDP%>%
  filter(PILLOUTDAY < 9000)%>%
  group_by(facility_type = as_factor(FACILITYTYPEGEN))%>%
  summarise(mean_days = mean(PILLOUTDAY))%>%
  ggplot() + geom_col(aes(x =  facility_type, y = mean_days)) +
coord_flip()
```

**B)** Suppose you suspect that the apparent difference between the facilities in A) is really a disparity between types of facilities that are most likely to be found in urban vs. rural areas. Create a pair of bar charts groups by URBAN to test if this is true. Are there differences between urban and rural facilities of each type?

```
SDP%>%
  filter(PILLOUTDAY < 9000)%>%
  group_by(facility_type = as_factor(FACILITYTYPEGEN), urban =
as_factor(URBAN))%>%
  summarize(mean_days = mean(PILLOUTDAY))%>%
  ggplot(aes(x = facility_type, y=mean_days)) + geom_col(aes(fill =
urban), position = position_dodge()) + coord_flip()
```

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Section 4

Use the SDP and HHF together

**Analyze the Sample – Part 4: Combining SDP and HHF Data**

Users should note that PMA2020 surveyed facilities in the same sampling areas as households and females in the same survey round. These SDP data are *not meant to be nationally representative.* Instead, they are meant to portray the health provision environment of the surveyed households and women. Thus, there are no sampling weights for SDP variables.

## Section 4

## Use the SDP and HHF together

The files do contain a weight for the sampling units EAWEIGHT, which is a probability weight representing the likelihood of the enumeration area (EA) being selected for sampling. The collectors of the original data do not recommend using EAWEIGHT to weight SDP variables. Rather, the best use of SDP variables is to calculate summary statistics at the EA level and attach them to the Household and Female (HHF) dataset using the EAID variable as a source of contextual information for each woman's service delivery environment.

For example, one could use the variables PILLOBS and PILLOUTDAY to calculate whether any facility in each EAID was out of stock of birth control pills and the mean number of days the facility or facilities in each EAID were out of stock of pills, respectively. These summary statistics may be merged with the HHF dataset in order to show whether each female respondent had reliable local access to birth control pills.

**A**) Create a table showing the number of women aged 15-49 (ELIGIBLE == 1) sampled in the Kenya 2016 Round 5 Household and Female dataset (HHF) who resided in each enumeration area where birth control pills were not available at all local facilities in the SDP survey. How many enumeration areas in Kenya 2016 meet these criteria?_____

```
HHF%>%
  mutate(pillobs = HHF$EAID %in% subset(SDP$EAID,
SDP$PILLOBS == 3))%>%
  group_by(EAID)%>%
  filter(pillobs==TRUE & ELIGIBLE==1)%>%
  count(pillobs)%>%
  select(EAID, n)
```

**B**) Looking at the table created in A), what is *the total number* of sampled women aged 15-49 (ELIGIBLE == 1) in the Kenya 2016 Round 5 Household and Female dataset (HHF) who resided in an enumeration area where birth control pills were not available at all local facilities in the SDP survey. _____

**C**) Run a logistic regression model to predict the association between women currently using the pill (FPNOWUSPILL) and the mean shortage duration (PILLOUTDAY) for each enumeration area that was out of pills on the day of the SDP interview. Adjust your model to be representative of all Kenyan women using FQWEIGHT. Recode values for

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Use the SDP and HHF together

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Complete!

Validate Your Answers Below

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Answers:

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Explore the Data

FPNOWUSPILL that are not in universe or missing to zero.

Is there an association between the number of days that the facilities in the woman's enumeration area are out of stock of pills and the woman's current use of the pill for family planning? _____

```
model_data <- HHF%>%
  left_join(SDP%>%
          group_by(EAID)%>%
          summarize(pilloutday = mean(subset(PILLOUTDAY,
PILLOUTDAY < 9000))))%>%
  mutate(fpnowuspill = case_when(as.numeric(FPNOWUSPILL) >
90 ~ 0, TRUE ~ as.numeric(FPNOWUSPILL)))%>%
  mutate(pilloutday = case_when(is.na(pilloutday) ~ 0, TRUE ~
pilloutday))

model <- glm(FPNOWUSPILL ~ pilloutday, data = model_data,
family = binomial, weights = round(FQWEIGHT))
summary(model)
exp(coef(model))
```

**ANSWERS - Analyze the sample - Part 1: Exploring Facility Types**

**A**) Create a frequency table for FACILITYTYPEGEN showing the proportion of each type of facility surveyed in Kenya 2016 Round 5.

```
SDP %>%
  count(type <- as_factor(FACILITYTYPEGEN)) %>%
  mutate(prop = prop.table(n))
```

```
> SDP %>%
+   count(type <- as_factor(FACILITYTYPEGEN)) %>%
+   mutate(prop = prop.table(n))
# A tibble: 7 x 3
  `type <- as_factor(FACILITYTYPEGEN)`      n    prop
  <fct>                                 <int>   <dbl>
1 Hospital                                 79 0.185
2 Health center                            90 0.210
3 Health clinic                            16 0.0374
4 Other health facility                     1 0.00234
5 Dispensary                              190 0.444
6 Pharmacy/chemist/drug shop               48 0.112
7 Other                                     4 0.00935
```

Answers:
Section 1
Explore the Data

**B**) According to the Universe tab, what facilities are included in the surveyed universe for FACILITYTYPEGEN? _*All service delivery points*_

**C**) Users should note that many variables in the service delivery point (SDP) survey have a universe defined by FACILITYADV, a country-specific designation of "advanced facility" types. Create a crosstab to see which types of facilities from the previous question were designated as "advanced facilities" in Kenya for 2016. _*All are advanced, except for Pharmacy / Chemist / Drug Shop*__

```
SDP %>%
  mutate(ADVANCED = FACILITYADV==1)%>%
  group_by(as_factor(FACILITYTYPEGEN), ADVANCED)%>%
  summarize()
```

```
> SDP %>%
+   mutate(ADVANCED = FACILITYADV==1)%>%
+   group_by(as_factor(FACILITYTYPEGEN), ADVANCED)%>%
+   summarize()
# A tibble: 7 x 2
# Groups:   as_factor(FACILITYTYPEGEN) [?]
  `as_factor(FACILITYTYPEGEN)` ADVANCED
  <fct>                        <lgl>
1 Hospital                     TRUE
2 Health center                TRUE
3 Health clinic                TRUE
4 Other health facility        TRUE
5 Dispensary                   TRUE
6 Pharmacy/chemist/drug shop   FALSE
7 Other                        TRUE
```

**D**) Consult the Comparability tab for FACILITYADV, taking care to note that advanced facility designations vary by country, and sometimes vary by survey round within a country. Locate the entry for Kenya, and determine whether its advanced facility designation matches what you found in Question C. Is the designation consistent for all Kenyan survey rounds that included this variable? _*It does match, and all Kenyan rounds interviewed have the same designation.*_

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Answers:
Section 2
Analyze the Data

**ANSWERS - Analyze the sample - Part 2: Descriptive Statistics**

**A**) Consider the variable PILLOBS, which describes whether the SDP had an observable stock of birth control pills on the day of the interview. According to the Codes tab, what are the possible responses for SDPs surveyed in Kenya 2016?

1 - *In-stock and observed*

2 - *In-stock but not observed*

Answers: Section 2 Analyze the Data

*3 - Out of stock*
*94 - Not interviewed (SDP questionnaire)*
*98 - No response or missing*
*99 - NIU (not in universe)*

**B**) According to the Comparability tab, possible responses to PILLOBS may vary from sample to sample. How so? *Some early samples include less detail, providing dichotomous responses based on whether the interviewer observed contraceptive pills in-stock. In these early samples, if contraceptive pills were not observed, they were assumed to be "out of stock". In later surveys, interviewers had the option of reporting that contraceptive pills were "in-stock but not observed".*

**C**) According to the Universe tab, what facilities are included in the surveyed universe for PILLOBS? *Service delivery points that provide contraceptive pills.*

**D**) Among facilities that usually provide birth control pills shown in PILLOBS, what type of facility was least likely to have supplies of birth control pills in-stock on the day of the interview? What proportion of facilities of this type were out of stock? (Restrict analysis only to completed interviews and in-universe cases). *Health clinics were most likely to be out of pills with 25% out of stock.* _

```
SDP%>%
  filter(PILLOBS < 90)%>%
  count(FACILITYTYPEGEN, PILLOBS)%>%
  group_by(FACILITYTYPEGEN)%>%
  mutate(type = as_factor(FACILITYTYPEGEN))%>%
  mutate(obs = as_factor(PILLOBS))%>%
  mutate(prop_type = prop.table(n))%>%
  select(type, obs, n, prop_type)
```

Answers:

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Analyze the Data

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Answers: Section 3

Visualize the Data

```
> SDP%>%
+   filter(PILLOBS < 90)%>%
+   count(FACILITYTYPEGEN, PILLOBS)%>%
+   group_by(FACILITYTYPEGEN)%>%
+   mutate(type = as_factor(FACILITYTYPEGEN))%>%
+   mutate(obs = as_factor(PILLOBS))%>%
+   mutate(prop_type = prop.table(n))%>%
+   select(type, obs, n, prop_type)
Adding missing grouping variables: `FACILITYTYPEGEN`
# A tibble: 17 x 5
# Groups:   FACILITYTYPEGEN [7]
   FACILITYTYPEGEN type                     obs                          n prop_type
   <int+lbl>       <fct>                    <fct>                    <int>     <dbl>
 1 1               Hospital                 In-stock and observed       69    0.896
 2 1               Hospital                 In-stock but not observed    1    0.0130
 3 1               Hospital                 Out of stock                 7    0.0909
 4 2               Health center            In-stock and observed       69    0.812
 5 2               Health center            In-stock but not observed    2    0.0235
 6 2               Health center            Out of stock                14    0.165
 7 3               Health clinic            In-stock and observed        8    0.667
 8 3               Health clinic            In-stock but not observed    1    0.0833
 9 3               Health clinic            Out of stock                 3    0.25
10 4               Other health facility    In-stock and observed        1    1
11 6               Dispensary               In-stock and observed      144    0.783
12 6               Dispensary               In-stock but not observed    3    0.0163
13 6               Dispensary               Out of stock                37    0.201
14 7               Pharmacy/chemist/drug shop In-stock and observed     36    0.878
15 7               Pharmacy/chemist/drug shop In-stock but not observed  2    0.0488
16 7               Pharmacy/chemist/drug shop Out of stock               3    0.0732
17 9               Other                    In-stock and observed        1    1
```

**ANSWERS - Analyze the sample - Part 3: Data Visualization**

A) For facilities that were out of birth control pills, PILLOUTDAY shows the number of days that supplies had been unavailable. Because some SDPs had been out of stock for more than 90 days, NIU and missing value codes for PILLOUTDAY are coded as values 9994, 9997, and 9999 in order to exceed the range of valid responses.

Calculate the mean shortage of pills for *all* in-universe facilities in PILLOUTDAY, taking care to exclude any value above 9000. Then find the mean for *each facility type* in FACILITYTYPEGEN, and display the result as a bar chart. (Restrict analysis only to valid responses from SDPs in universe for PILLOUTDAY).

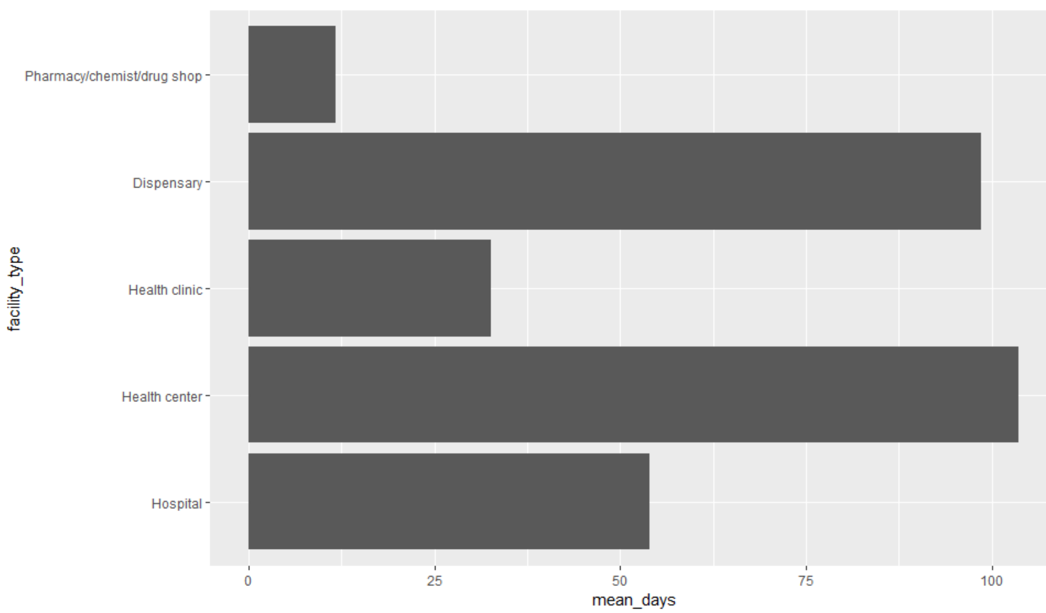
```
SDP%>%
  filter(PILLOUTDAY < 9000)%>%
  group_by(facility_type = as_factor(FACILITYTYPEGEN),
urban = as_factor(URBAN))%>%
  summarize(mean_days = mean(PILLOUTDAY))%>%
  ggplot(aes(x = facility_type, y=mean_days)) +
geom_col(aes(fill = urban), position = position_dodge()) +
coord_flip()
```

Answers: Section 3

Visualize the Data

```
> SDP%>%
+   filter(PILLOUTDAY < 9000)%>%
+   summarise(mean(PILLOUTDAY))
# A tibble: 1 x 1
  `mean(PILLOUTDAY)`
               <dbl>
1               87.5
```

```
> SDP%>%
+   filter(PILLOUTDAY < 9000)%>%
+   group_by(facility_type = as_factor(FACILITYTYPEGEN), urban = as_factor(URBAN))%>%
+   summarize(mean(PILLOUTDAY))
# A tibble: 10 x 3
# Groups:   facility_type [?]
   facility_type              urban `mean(PILLOUTDAY)`
   <fct>                      <fct>              <dbl>
 1 Hospital                   Rural               38.6
 2 Hospital                   Urban               92.5
 3 Health center              Rural               98.8
 4 Health center              Urban              110.
 5 Health clinic              Rural                1
 6 Health clinic              Urban               48.5
 7 Dispensary                 Rural              104.
 8 Dispensary                 Urban               80.9
 9 Pharmacy/chemist/drug shop Rural               17
10 Pharmacy/chemist/drug shop Urban                1
```

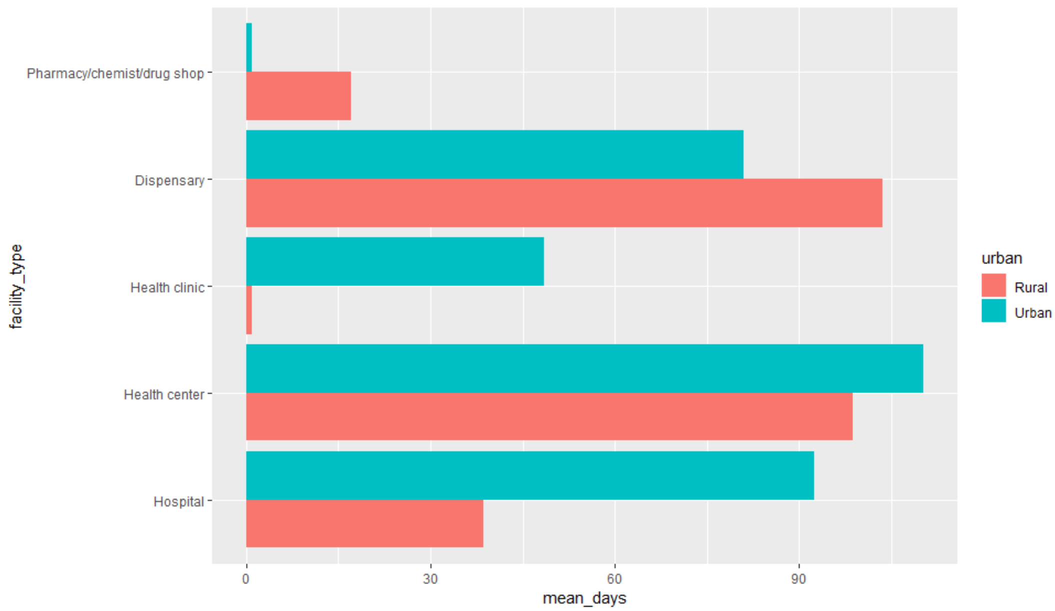



**B)** Suppose you suspect that the apparent difference between the facilities in A) is really a disparity between types of facilities that are most likely to be found in urban vs. rural areas. Create a pair of bar charts groups by URBAN to test if this is true. Are there differences between urban and rural facilities of each type?

Answers: Section 3

Visualize the Data

```
SDP%>%
  filter(PILLOUTDAY < 9000)%>%
  group_by(facility_type = as_factor(FACILITYTYPEGEN), urban =
as_factor(URBAN))%>%
  summarize(mean_days = mean(PILLOUTDAY))%>%
  ggplot(aes(x = facility_type, y=mean_days)) + geom_col(aes(fill =
urban), position = position_dodge()) + coord_flip()
```

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Answers: Section 4

Use the SDP and HHF together

**ANSWERS - Analyze the Sample – Part 4: Combining SDP and HHF Data**

Users should note that PMA2020 surveyed facilities in the same sampling areas as households and females in the same survey round. These SDP data are *not meant to be nationally representative.* Instead, they are meant to portray the health provision environment of the surveyed households and women. Thus, there are no sampling weights for SDP variables.

The files do contain a weight for the sampling units EAWEIGHT, which is a probability weight representing the likelihood of the enumeration area (EA) being selected for sampling. The collectors of the original data do not recommend using EAWEIGHT to weight SDP variables. Rather, the best use of SDP variables is to calculate summary statistics at the EA level and attach them to the Household and Female (HHF) dataset using the EAID variable as a source of

## Answers: Section 4

## Use the SDP and HHF together

contextual information for each woman's service delivery environment.

For example, one could use the variables PILLOBS and PILLOUTDAY to calculate whether any facility in each EAID was out of stock of birth control pills and the mean number of days the facility or facilities in each EAID were out of stock of pills, respectively. These summary statistics may be merged with the HHF dataset in order to show whether each female respondent had reliable local access to birth control pills.

**A**) Create a table showing the number of women aged 15-49 (ELIGIBLE == 1) sampled in the Kenya 2016 Round 5 Household and Female dataset (HHF) who resided in each enumeration area where birth control pills were not available at all local facilities in the SDP survey. How many enumeration areas in Kenya 2016 meet these criteria?

*43 enumeration areas*

```
HHF%>%
  mutate(pillobs = HHF$EAID %in% subset(SDP$EAID,
SDP$PILLOBS == 3))%>%
  group_by(EAID)%>%
  filter(pillobs==TRUE & ELIGIBLE==1)%>%
  count(pillobs)%>%
  select(EAID, n)
```

Answers: Section 4

Use the SDP and HHF together

```
> HHF%>%
+   mutate(pillobs = HHF$EAID %in% subset(SDP$EAID, SDP$PILLOBS == 3))%>%
+   group_by(EAID)%>%
+   filter(pillobs==TRUE & ELIGIBLE==1)%>%
+   count(pillobs)%>%
+   select(EAID, n)
# A tibble: 43 x 2
# Groups:   EAID [43]
    EAID     n
   <dbl> <int>
 1  4013    33
 2  4047    44
 3  4163    47
 4  4207    38
 5  4212    23
 6  4214    38
 7  4234    50
 8  4245    45
 9  4318    36
10  4336    41
11  4356    47
12  4361    45
13  4373    39
14  4431    40
15  4456    50
16  4485    51
17  4531    42
18  4626    23
19  4628    27
20  4639    36
21  4655    39
22  4662    34
23  4676    56
24  4677    44
25  4707    56
26  4711    44
27  4712    22
28  4719    46
29  4760    52
30  4768    29
31  4784    50
32  4795    63
33  4871    51
34  4885    25
35  4887    45
36  4895    55
37  4899    34
38  4905    38
39  4938    36
40  4952    54
41  4963    39
42  4965    36
43  4974    34
```

**B**) Looking at the table created in A), what is *the total number* of sampled women aged 15-49 (ELIGIBLE == 1) in the Kenya 2016 Round 5 Household and Female dataset (HHF) who resided in an enumeration area where birth control pills were not available at all local facilities in the SDP survey?

*These are the first three EAIDs in the list:*

*EAID 4013 = 33 women*

*EAID 4047 = 44 women*

*EAID 4163 = 47 women*

Answers: Section 4

Use the SDP and HHF together

**C**) Run a logistic regression model to predict the association between women currently using the pill (FPNOWUSPILL) and the mean shortage duration (PILLOUTDAY) for each enumeration area that was out of pills on the day of the SDP interview. Adjust your model to be representative of all Kenyan women using FQWEIGHT. Recode values for FPNOWUSPILL that are not in universe or missing to zero. Is there such an association?

*The likelihood that a sampled woman uses birth control pills remains the same regardless of the average number of days that her local SDP had none available (odds ratio = 1.000). However, this finding is not statistically significant (p = 0.728).*

```
model_data <- HHF%>%
  left_join(SDP%>%
            group_by(EAID)%>%
            summarize(pilloutday = mean(subset(PILLOUTDAY,
PILLOUTDAY < 9000))))%>%
  mutate(fpnowuspill = case_when(as.numeric(FPNOWUSPILL) >
90 ~ 0, TRUE ~ as.numeric(FPNOWUSPILL)))%>%
  mutate(pilloutday = case_when(is.na(pilloutday) ~ 0, TRUE ~
pilloutday))

model <- glm(FPNOWUSPILL ~ pilloutday, data = model_data,
family = binomial, weights = round(FQWEIGHT))
summary(model)
exp(coef(model))
```

## Answers: Section 4

Use the SDP and HHF together

```
> model_data <- HHF%>%
+   left_join(SDP%>%
+               group_by(EAID)%>%
+               summarize(pilloutday = mean(subset(PILLOUTDAY, PILLOUTDAY < 9000))))%>%
+   mutate(fpnowuspill = case_when(as.numeric(FPNOWUSPILL) > 90 ~ 0, TRUE ~ as.numeric(FPNOWUSPILL)))%>%
+   mutate(pilloutday = case_when(is.na(pilloutday) ~ 0, TRUE ~ pilloutday))
Joining, by = "EAID"
>
> model <- glm(FPNOWUSPILL ~ pilloutday, data = model_data, family = binomial, weights = round(FQWEIGHT))
> summary(model)

Call:
glm(formula = FPNOWUSPILL ~ pilloutday, family = binomial, data = model_data,
    weights = round(FQWEIGHT))

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.5405   0.0000   0.0000   0.0000   4.2755

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -2.9979074  0.0649217 -46.177   <2e-16 ***
pilloutday  -0.0003712  0.0010675  -0.348    0.728
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 2378.5  on 5521  degrees of freedom
Residual deviance: 2378.4  on 5520  degrees of freedom
AIC: 2382.4

Number of Fisher Scoring iterations: 5

> exp(coef(model))
(Intercept)  pilloutday
 0.04989136  0.99962886
```

| FPNOWUSPILL | Odds Ratio | P value | 95% CI |
|---|---|---|---|
| PILLOUTDAY | 1.000 | 0.728 | (0.998, 1.002) |