CONTENTS

1 INTRODUCTION

Performance Monitoring for Action (PMA) uses innovative mobile technology to support low-cost, rapid-turnaround surveys that monitor key health and development indicators.

PMA surveys collect longitudinal data throughout a country at the household and health facility levels by female data collectors, known as resident enumerators, using mobile phones. The survey collects information from the same women and households over time for regular tracking of progress and for understanding the drivers of contraceptive use dynamics. The data are rapidly validated, aggregated, and prepared into tables and graphs, making results quickly available to stakeholders. PMA surveys can be integrated into national monitoring and evaluation systems using a low-cost, rapid-turnaround survey platform that can be adapted and used for various health data needs.

The PMA project is implemented by local partner universities and research organizations who train and deploy the cadres of female resident enumerators.

The purpose of this manual is to provide guidance on the analysis of **harmonized longitudinal data** for a panel of women age 15-49 surveyed by PMA and published in partnership with IPUMS PMA. IPUMS provides census and survey products from around the world in an integrated format, making it easy to compare data from multiple countries. IPUMS PMA data are available free of charge, subject to terms and conditions: please register here to request access to the data featured in this guide.

PMA has also published a guide to **cross-sectional** analysis in both English and French.

This manual provides reproducible coding examples in the statistical programming language R. Each chapter also appears as a post on the IPUMS PMA data analysis blog, where you'll find new content posted every two weeks.

Stata users: a companion manual for IPUMS PMA longitudinal analysis is also available with coding examples written in Stata.

1.1 IPUMS PMA DATA IN R

The first two chapters of this manual introduce new users to PMA longitudinal data and the IPUMS PMA website, respectively. After demonstrating how to obtain an IPUMS PMA data extract, the remaining chapters feature extensive data analysis examples written in R.

To follow along, you'll need to download the appropriate version of R for your computer's operating system at https://www.r project.org/. **R is available at no cost** and it runs on a wide variety of UNIX platforms, Windows, and MacOS. We also recommend downloading a free copy of RStudio, an integrated development environment (IDE) designed to make your experience with R much easier.

© R-project.org
(GPL-2 | GPL-3)

Individual chapters may introduce one or two **R packages** that provide helpful functions for longitudinal survey analysis, in particular. Two packages we feature in *every* chapter are ipumsr and tidyverse. You can install these and other packages featured in this guide like so:

```
install.packages("ipumsr")
install.packages("tidyverse")
```

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The `ipumsr` package is designed to help R users import and explore data extracts downloaded from IPUMS. As we'll see, categorical variables from IPUMS appear as **labelled integers** represented in R by a number and a label:

```
# A tibble: 4 × 2
  COUNTRY                          n
  <int+lbl>                    <int>
1 1 [Burkina Faso]              8257
2 2 [Congo, Democratic Republic] 6090
3 7 [Kenya]                    12605
4 9 [Nigeria]                   3225
```

The `tidyverse` is actually a collection of packages developed in-part by contributors at RStudio. These include:

- ggplot2 for data visualisation
- dplyr for data manipulation
- tidyr for data tidying
- readr for data import
- purrr for functional programming
- tibble for tibbles, a modern re-imagining of data frames
- stringr for strings
- forcats for factors

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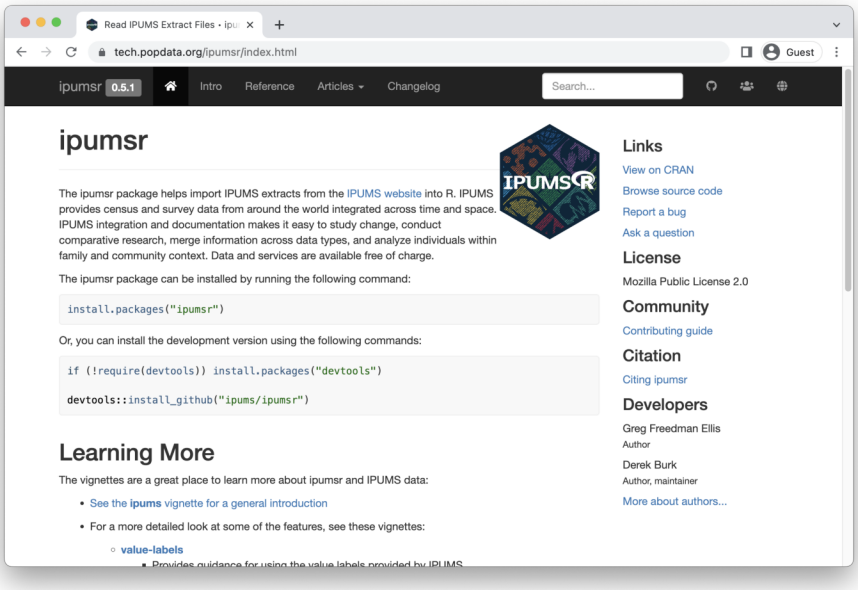
1.2 RESOURCES FOR R USERS

This manual focuses exclusively on longitudinal family planning data from IPUMS PMA, but the companion data analysis blog covers a wide range of topics like:

- A free online course for beginners
- New data announcements
- Data cleaning and reformatting
- Data analysis and visualization
- Spatial analysis
- Guides to PMA Service Delivery Point & Client Exit Interview data

Beyond the blog, it's important to know where to find **instructions and examples** for the R packages featured in this guide. Nearly all of these packages have a dedicated website with a homepage, reference page (documentation for individual functions), collection of articles (for general instructions), and changelog (for news about updates). The ipumsr page is a great place to start:



Finally, if you're looking for a more general introduction to R, we strongly recommend the following **free resources**:

- R for Data Science for beginners
- Advanced R for a deeper dive
- RSpatial for analysis with spatial data
- ggplot2 for data visualization
- R Markdown: The Definitive Guide for producing annotated code, word documents, presentations, web pages, and more
- R-bloggers for regular news and tutorials

1.3 PMA BACKGROUND

Dating back to 2013, the original PMA survey design included high-frequency, **cross-sectional** samples of women and service delivery points collected from eleven countries participating in Family Planning 2020 (FP2020) - a global partnership that supports the rights of women and girls to decide for themselves whether, when, and how many children they want to have. These surveys were designed to monitor annual progress towards FP2020 goals via population-level estimates for several core indicators.

Beginning in 2019, PMA surveys were redesigned under a renewed partnership called Family Planning 2030 (FP2030). These new surveys have been refocused on reproductive and sexual health indicators, and they feature a **longitudinal panel** of women of childbearing age. This design will allow researchers to measure contraceptive dynamics and changes in women's fertility intentions over a **three year period** via annual in-person interviews.[1]

Questions on the redesigned survey cover topics like:

- awareness, perception, knowledge, and use of contraceptive methods
- perceived quality and side effects of contraceptive methods among current users
- birth history and fertility intentions
- aspects of health service provision
- domains of empowerment

[1] In addition to these three in-person surveys, PMA also conducted telephone interviews with panel members focused on emerging issues related to the COVID-19 pandemic in 2020. These telephone surveys are already available for several countries - see our series on PMA COVID-19 surveys for details.

1.4 SAMPLING

PMA panel data includes a mixture of **nationally representative** and **sub-nationally representative** samples. The panel study consists of three data collection phases, each spaced one year apart.

As of this writing, IPUMS PMA has released data from the first *two* phases for four countries where Phase 1 data collection began in 2019; IPUMS PMA has released data from only the *first* phase for three countries where Phase 1 data collection began in August or September 2020. Phase 3 data collection and processing is currently underway.

		Now Available from IPUMS PMA		
Sample	Phase 1 Data Collection*	Phase 1	Phase 2	Phase 3
Burkina Faso	Dec 2019 - Mar 2020	x	x	
Cote d'Ivoire	Sep 2020 - Dec 2020	x		
DRC - Kinshasa	Dec 2019 - Feb 2020	x	x	
DRC - Kongo Central	Dec 2019 - Feb 2020	x	x	
India - Rajasthan	Aug 2020 - Oct 2020	x		
Kenya	Nov 2019 - Dec 2019	x	x	
Nigeria - Kano	Dec 2019 - Jan 2020	x	x	
Nigeria - Lagos	Dec 2019 - Jan 2020	x	x	
Uganda	Sep 2020 - Oct 2020	x		

** Each data collection phase is spaced one year apart*

PMA uses a multi-stage clustered sample design, with stratification at the urban-rural level or by sub-region. Sample clusters - called enumeration areas (EAs) – are provided by the national statistics agency in each country.[2] These EAs are sampled using a *probability proportional to size* (PPS) method relative to the population distribution in each stratum.

Resident enumerators are women over age 21 living in (or near) each EA who hold at least a high school diploma.

[2] Displaced GPS coordinates for the centroid of each EA are available for most samples by request from PMA. IPUMS PMA provides shapefiles for PMA countries here.

At Phase 1, 35 household dwellings were selected at random within each EA. Resident enumerators visited each dwelling and invited one household member to complete a Household Questionnaire[3] that includes a census of all household members and visitors who stayed there during the night before the interview. Female household members and visitors aged 15-49 were then invited to complete a subsequent Phase 1 Female Questionnaire.[4]

One year later, resident enumerators visited the same dwellings and administered a Phase 2 Household Questionnaire. A panel member in Phase 2 is any woman still age 15-49 who could be reached for a second Female Questionnaire, either because:

- she still lived there, or
- she had moved elsewhere within the study area,[5] but at least one member of the Phase 1 household remained and could help resident enumerators locate her new dwelling.[6]

SAMEDWELLING indicates whether a Phase 2 female respondent resided in her Phase 1 dwelling or a new one.

PANELWOMAN indicates whether a Phase 2 household member completed the Phase 1 Female Questionnaire.

Additionally, resident enumerators administered the Phase 2 Female Questionnaire to *new* women in sampled households who:

- reached age 15 after Phase 1
- joined the household after Phase 1
- declined the Female Questionnaire at Phase 1, but agreed to complete it at Phase 2

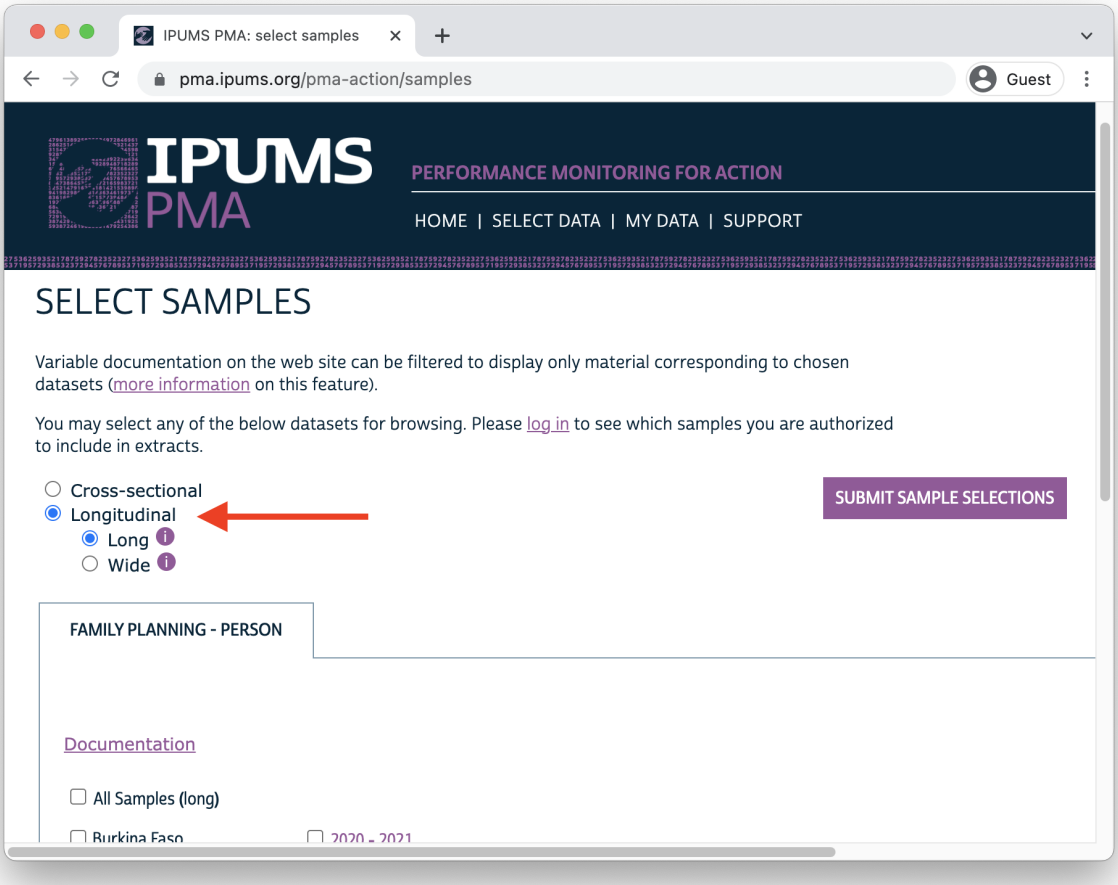
[3] Questionnaires administered in each country may vary from this **Core Household Questionnaire** - click here for details.

[4] Questionnaires administered in each country may vary from this **Core Female Questionnaire** - click here for details.

[5] The "study area" is area within which resident enumerators should attempt to find panel women that have moved out of their Phase 1 dwelling. This may extend beyond the woman's original EA as determined by in-country administrators - see PMA Phase 2 and Phase 3 Survey Protocol for details.

[6] In cases where no Phase 1 household members remained in the dwelling at Phase 2, women from the household are considered lost to follow-up (LTFU). A panel member is also considered LTFU if a Phase 2 Household Questionnaire was not completed, if she declined to participate, or if she was deceased or otherwise unavailable.

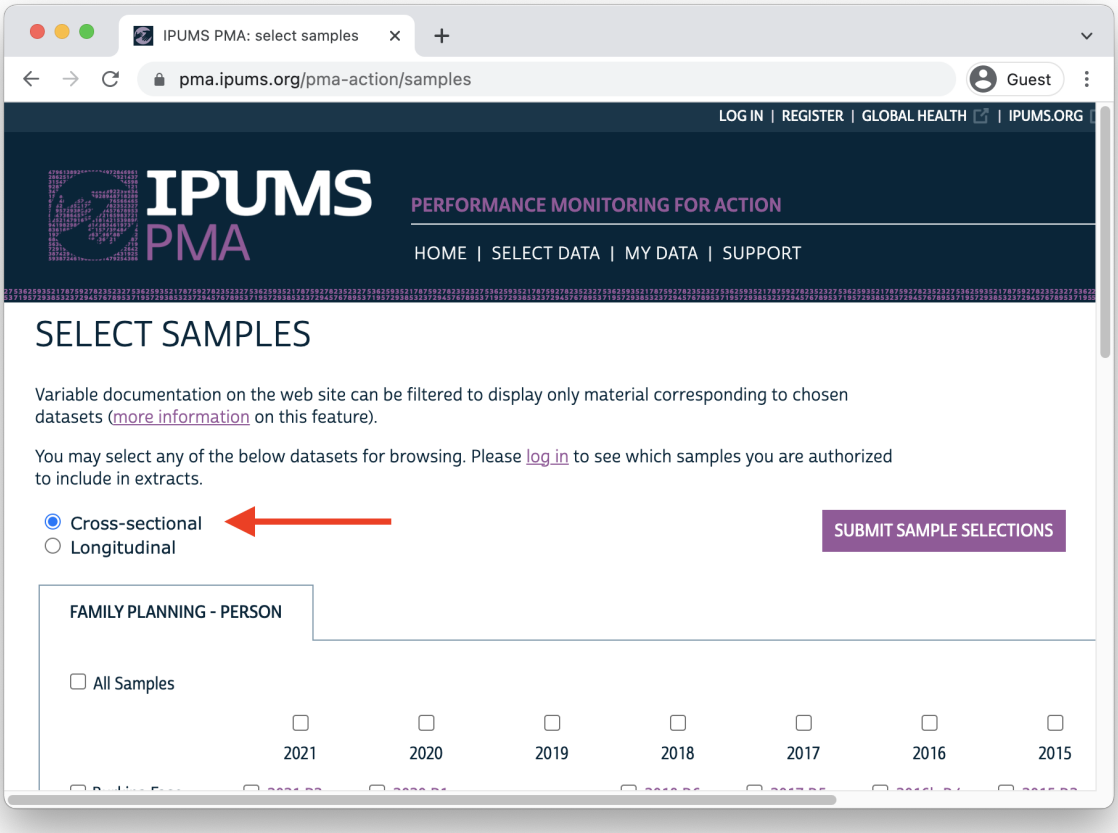
When you select the new **Longitudinal** sample option at checkout, you'll be able to include responses from every available phase of the study. These samples are available in either "long" format (responses from each phase will be organized in separate rows) or "wide" format (responses from each phase will be organized in columns).



In addition to following up with women in the panel over time, PMA also adjusted sampling so that a cross-sectional sample could be produced concurrently with each data collection phase. These samples mainly overlap with the data you'll obtain for a particular phase in the longitudinal sample, except that replacement households were drawn from each EA where more than 10% of households from the previous phase were no longer there. Conversely, panel members who were located in a new dwelling at Phase 2 will not be represented in the cross-sectional sample drawn from that EA. These adjustments ensure that population-level indicators may be derived from cross-sectional samples in a given year, even if panel members move or are lost to follow-up.

CROSS_SECTION indicates whether a household member in a longitudinal sample is also included in the cross-sectional sample for a given year (every person in a cross-sectional sample is included in the longitudinal sample).

You'll find PMA cross-sectional samples dating back to 2013 if you select the **Cross-sectional** sample option at checkout.



1.5 SURVEY DESIGN ELEMENTS

Throughout this guide, we'll demonstrate how to incorporate PMA sampling weights and information about its stratified cluster sampling procedure into your analysis. To do so, we'll rely on tools from the srvyr package.[7]

You can install or update `srvyr` like so:

```
install.packages("srvyr")
```

To use `srvyr` and other `tidyverse` packages in an R session, load them with the library function:

```
library(srvyr)
library(ipumsr)
library(tidyverse)
```

We'll demonstrate how to obtain an IPUMS PMA data extract in the next chapter. For now, let's assume that we've got a wide-format[8] data extract loaded into R as an object named `dat`. In this example, we'll feature data collected from the first two phases of the Burkina Faso panel. These data will be organized in a tidy table - a tibble - that looks like this:

```
dat
```

```
# A tibble: 5,212 × 138
  SAMPLE_1       SAMPLE_2    COUNTRY YEAR_1 YEAR_2 HHID_1 HHID_2 RESPO…¹ RESPO…² ELIGI…³
  <int+lbl>      <int+lbl>   <int+l>  <int>  <int> <chr>  <chr>  <int+l> <int+l> <int+l>
1 85409 [Burkin… 85412 [Bur… 1 [Bur…   2019   2021 85420… 85420… 0 [No]  0 [No]  1 [Yes…
2 85409 [Burkin… 85412 [Bur… 1 [Bur…   2019   2021 85420… 85420… 0 [No]  1 [Yes] 1 [Yes…
3 85409 [Burkin… 85412 [Bur… 1 [Bur…   2019   2021 85420… 85420… 0 [No]  0 [No]  1 [Yes…
# … with 5,209 more rows, 128 more variables: ELIGIBLE_2 <int+lbl>, LINENO_1 <int>,
#   LINENO_2 <int>, STRUCTURNO_1 <dbl+lbl>, STRUCTURNO_2 <dbl+lbl>, HHNUM_1 <dbl>,
#   HHNUM_2 <dbl>, EAID_1 <dbl>, EAID_2 <dbl>, ENUMID_1 <dbl+lbl>, ENUMID_2 <dbl+lbl>,
#   CONSENTFQ_1 <int+lbl>, CONSENTFQ_2 <int+lbl>, AVAILABLEFQ_1 <int+lbl>,
#   AVAILABLEFQ_2 <int+lbl>, FQACQUAINTED_1 <int+lbl>, FQACQUAINTED_2 <int+lbl>,
#   VISITNUMFQ_1 <int+lbl>, VISITNUMFQ_2 <int+lbl>, RESULTFQ_1 <int+lbl>,
#   RESULTFQ_2 <int+lbl>, CROSS_SECTION_1 <int+lbl>, CROSS_SECTION_2 <int+lbl>, …
```

[7] The `srvyr` package is a tidy implementation of the popular survey package for R, authored by Dr. Thomas Lumley. For thorough discussion of the types of weights available in both R and Stata, we recommend this blog post by Dr. Lumley.

[8] As we will see in Chapter 2, IPUMS PMA publishes longitudinal data in both "wide" (one row per woman) and "long" (one row per phase) format.

1.5.1 Survey Weights

Whether you intend to work with a new **Longitudinal** or **Cross-sectional** data extract, you'll find the same set of sampling weights available for all PMA Family Planning surveys dating back to 2013:

- HQWEIGHT can be used to generate cross-sectional population estimates from questions on the Household Questionnaire.[10]
- FQWEIGHT can be used to to generate cross-sectional population estimates from questions on the Female Questionnaire.[11]
- EAWEIGHT can be used to compare the selection probability of a particular household with that of its EA.

A fourth Family Planning survey weight, POPWT, is currently available only for **Cross-sectional** data extracts.[9]

Additionally, PMA created a new weight, PANELWEIGHT, which should be used in longitudinal analyses spanning multiple phases, as it adjusts for loss to follow-up. `PANELWEIGHT` is available only for **Longitudinal** data extracts.

For example, suppose we wanted to estimate the proportion of reproductive age women in Burkina Faso who were using contraception at the time of data collection for both Phase 1 and Phase 2. In a cross-sectional or "long" longitudinal extract, you'll find this information in the variable CP. In the "wide" extract featured here, you'll find it in `CP_1` for Phase 1, and in `CP_2` for Phase 2.

Variable names in a "wide" extract have a numeric suffix for their data collection phase. `CP_1` is the Phase 1 version of CP, while `CP_2` comes from Phase 2.

```
dat %>% count(CP_1, CP_2)
```

```
# A tibble: 5 × 3
  CP_1                                CP_2          n
  <int+lbl>                           <int+lbl> <int>
1  0 [No]                             0 [No]     2589
2  0 [No]                             1 [Yes]     821
3  1 [Yes]                            0 [No]      556
4  1 [Yes]                            1 [Yes]    1241
5 99 [NIU (not in universe) or missing] 0 [No]        5
```

[9] `POPWT` can be used to estimate population-level *counts* - click here or view this video for details.

[10] `HQWEIGHT` reflects the calculated selection probability for a household in an EA, normalized at the population-level. Users intending to estimate population-level indicators for *households* should restrict their sample to one person per household via LINENO - see household weighting guide for details.

[11] `FQWEIGHT` adjusts `HQWEIGHT` for female non-response within the EA, normalized at the population-level - see female weighting guide for details.

The `srvyr` package provides two functions we'll need to obtain our population estimate. The first, as_survey_design, allows us to specify `PANELWEIGHT` as a sampling weight. The second, survey_mean, uses that weight in an estimating function; in this case, we'll get the estimated proportion where `CP_1` and `CP_2` both have the value `1 [Yes]` after removing missing / NIU responses with `CP_1 < 90 & CP_2 < 90`.

In subsequent chapters, we'll use `vartype = "ci"` to include a 95% confidence interval set by `level = 0.95` any time we calculate a population estimate. For discrete variables, we'll also include `proportion = TRUE` and `prop_method = "logit"`. In practice, there are large number of ways to calculate a confidence interval for a proportion.[12] The srvyr package includes several options for `prop_method`,[13] but we'll use these settings because:

1. they ensure that each proportion's confidence interval only includes values between 0% and 100%,
2. they will include the real-world population proportion close to 95% of the time,
3. the `logit` method yields a relatively narrow interval compared with other options, and
4. these intervals will match the default intervals reported by Stata and SPSS survey proportion functions.

```
dat %>%
  as_survey_design(weight = PANELWEIGHT) %>%
  filter(CP_1 < 90 & CP_2 < 90) %>%
  summarise(
    survey_mean(
      CP_1 * CP_2,
      vartype = "ci",
      level = 0.95,
      proportion = TRUE,
      prop_method = "logit"
    )
  )
```

`coef` shows the estimated population proportion

`_low` and `_upp` show the lower and upper bounds of a 95% confidence interval

```
# A tibble: 1 × 3
   coef `_low` `_upp`
  <dbl>  <dbl>  <dbl>
1 0.188  0.174  0.203
```

[12] See Dean & Pagano [-@Dean-Pagano] for discussion.

[13] See svyciprop for a complete list of methods.

1.5.2 Sample Clusters

You can also provide information about sample clusters via as_survey_design. In general, we expect households selected from the same EA to share certain characteristics, such that some degree of variation seen in a variable of interest may be non-random at the EA-level. To compensate, you may wish the expand the standard errors produced by `survey_mean` by providing EA identifiers in EAID.

Here, we include `id = EAID_1`.[14] Compared with our original estimate, notice that the 95% confidence interval for our contraceptive use estimate is wider when we provide information about the clustered sample design - these are "cluster-robust" standard errors.

```
dat %>%
  as_survey_design(weight = PANELWEIGHT, id = EAID_1) %>%
  filter(CP_1 < 90 & CP_2 < 90) %>%
  summarise(
    survey_mean(
      CP_1 * CP_2,
      vartype = "ci",
      level = 0.95,
      proportion = TRUE,
      prop_method = "logit"
    )
  )
```

```
# A tibble: 1 × 3
   coef `_low` `_upp`
  <dbl>  <dbl>  <dbl>
1 0.188  0.163  0.215
```

[14] As we'll see in an upcoming post, women are considered "lost to follow-up" if they moved outside the study area after Phase 1. Therefore, `EAID_1` and `EAID_2` are identical for all panel members: you can use either one to identify sample clusters.

1.5.3 Sample Strata

Finally, we'll also use as_survey_design to specify sample strata. For most samples, including Burkina Faso, this information is included in the variable STRATA. We'll include it here with `strata = STRATA_1`.[15]

```
dat %>%
  as_survey_design(weight = PANELWEIGHT, id = EAID_1, strata = STRATA_1) %>%
  filter(CP_1 < 90 & CP_2 < 90) %>%
  summarise(
    survey_mean(
      CP_1 * CP_2,
      vartype = "ci",
      level = 0.95,
      proportion = TRUE,
      prop_method = "logit"
    )
  )
```

```
# A tibble: 1 × 3
   coef `_low` `_upp`
  <dbl>  <dbl>  <dbl>
1 0.188  0.164  0.214
```

[15] As with EAID, you may use either STRATA_1 or STRATA_2 if your analysis is restricted to panel members.

The variable STRATA is *not available* for samples collected from DRC - Kinshasa or DRC - Kongo Central. If your extract includes any DRC sample, you'll need to amend this variable to include one unique numeric code for each of those regions.

For example, let's look at a different "wide" extract, `dat2`, containing all of the samples included in this data release. Notice that `STRATA_1` lists the sample strata for every COUNTRY *except* for DRC, where you see the value `NA`.

```
dat2 %>% count(COUNTRY, STRATA_1)
```

```
# A tibble: 27 × 3
   COUNTRY                        STRATA_1                              n
   <int+lbl>                      <int+lbl>                         <int>
 1 1 [Burkina Faso]               85401 [Urban, Burkina Faso]        3058
 2 1 [Burkina Faso]               85402 [Rural, Burkina Faso]        2154
 3 2 [Congo, Democratic Republic]    NA                              3487
 4 7 [Kenya]                      40410 [Bungoma – urban, Kenya]      153
 5 7 [Kenya]                      40411 [Bungoma – rural, Kenya]      489
 6 7 [Kenya]                      40412 [Kakamega – urban, Kenya]     133
 7 7 [Kenya]                      40413 [Kakamega – rural, Kenya]     438
 8 7 [Kenya]                      40414 [Kericho – urban, Kenya]      249
 9 7 [Kenya]                      40415 [Kericho – rural, Kenya]      453
10 7 [Kenya]                      40416 [Kiambu – urban, Kenya]       214
11 7 [Kenya]                      40417 [Kiambu – rural, Kenya]       311
12 7 [Kenya]                      40418 [Kilifi – urban, Kenya]       170
13 7 [Kenya]                      40419 [Kilifi – rural, Kenya]       455
14 7 [Kenya]                      40420 [Kitui – urban, Kenya]        153
15 7 [Kenya]                      40421 [Kitui – rural, Kenya]        586
16 7 [Kenya]                      40422 [Nairobi – urban, Kenya]      494
17 7 [Kenya]                      40423 [Nandi – urban, Kenya]        260
18 7 [Kenya]                      40424 [Nandi – rural, Kenya]        711
19 7 [Kenya]                      40425 [Nyamira – urban, Kenya]      143
20 7 [Kenya]                      40426 [Nyamira – rural, Kenya]      382
21 7 [Kenya]                      40427 [Siaya – urban, Kenya]        130
22 7 [Kenya]                      40428 [Siaya – rural, Kenya]        437
23 7 [Kenya]                      40429 [West Pokot – urban, Kenya]   104
24 7 [Kenya]                      40430 [West Pokot – rural, Kenya]   474
25 9 [Nigeria]                    56606 [Lagos, Nigeria]             1089
26 9 [Nigeria]                    56611 [Kano – Urban]                437
27 9 [Nigeria]                    56612 [Kano – Rural]                561
```

Now let's see what happens when we try to produce population-level estimates with STRATA_1:

```
dat2 %>%
  as_survey_design(weight = PANELWEIGHT, id = EAID_1, strata = STRATA_1) %>%
  filter(CP_1 < 90 & CP_2 < 90) %>%
  group_by(COUNTRY, GEOCD, GEONG) %>%
  summarise(
    survey_mean(
      CP_1 * CP_2,
      vartype = "ci",
      level = 0.95,
      proportion = TRUE,
      prop_method = "logit"
    )
  )
```

```
Error in (function (object, ...) : missing values in `strata'
```

This fails because as_survey_design encounters NA values in STRATA_1. Fortunately, we can replace those values with numeric codes from the variable GEOCD:

```
dat2 %>% count(GEOCD)
```

```
# A tibble: 3 × 2
  GEOCD                   n
  <int+lbl>           <int>
1  1 [Kinshasa]        1973
2  2 [Kongo Central]   1514
3 NA                  14238
```

If GEOCD is not NA, we'll use its numeric code in place of STRATA_1. Otherwise, we'd like to leave STRATA_1 unchanged. However, because both variables include *value labels*, we'll first need remove them with as.numeric. To avoid confusion with the original variable STRATA_1, we'll call our new variable STRATA_RECODE.

```
dat2 <- dat2 %>%
  mutate(
    STRATA_RECODE = if_else(
      is.na(GEOCD),
      as.numeric(STRATA_1),
      as.numeric(GEOCD)
    )
  )
```

Notice that `STRATA_RECODE` replaces the `NA` values in `STRATA_1`, leaving its numeric values unchanged.

```
dat2 %>% count(GEOCD, STRATA_1, STRATA_RECODE)
```

```
# A tibble: 28 × 4
   GEOCD              STRATA_1                          STRATA_RECODE     n
   <int+lbl>          <int+lbl>                                 <dbl> <int>
 1  1 [Kinshasa]        NA                                         1  1973
 2  2 [Kongo Central]   NA                                         2  1514
 3 NA                 40410 [Bungoma – urban, Kenya]            40410   153
 4 NA                 40411 [Bungoma – rural, Kenya]            40411   489
 5 NA                 40412 [Kakamega – urban, Kenya]           40412   133
 6 NA                 40413 [Kakamega – rural, Kenya]           40413   438
 7 NA                 40414 [Kericho – urban, Kenya]            40414   249
 8 NA                 40415 [Kericho – rural, Kenya]            40415   453
 9 NA                 40416 [Kiambu – urban, Kenya]             40416   214
10 NA                 40417 [Kiambu – rural, Kenya]             40417   311
11 NA                 40418 [Kilifi – urban, Kenya]             40418   170
12 NA                 40419 [Kilifi – rural, Kenya]             40419   455
13 NA                 40420 [Kitui – urban, Kenya]              40420   153
14 NA                 40421 [Kitui – rural, Kenya]              40421   586
15 NA                 40422 [Nairobi – urban, Kenya]            40422   494
16 NA                 40423 [Nandi – urban, Kenya]              40423   260
17 NA                 40424 [Nandi – rural, Kenya]              40424   711
18 NA                 40425 [Nyamira – urban, Kenya]            40425   143
19 NA                 40426 [Nyamira – rural, Kenya]            40426   382
20 NA                 40427 [Siaya – urban, Kenya]              40427   130
21 NA                 40428 [Siaya – rural, Kenya]              40428   437
22 NA                 40429 [West Pokot – urban, Kenya]         40429   104
23 NA                 40430 [West Pokot – rural, Kenya]         40430   474
24 NA                 56606 [Lagos, Nigeria]                    56606  1089
25 NA                 56611 [Kano – Urban]                      56611   437
26 NA                 56612 [Kano – Rural]                      56612   561
27 NA                 85401 [Urban, Burkina Faso]               85401  3058
28 NA                 85402 [Rural, Burkina Faso]               85402  2154
```

Now, we can use STRATA_RECODE with as_survey_design to obtain population estimates for each nationally representative or sub-nationally representative sample.

```
dat2 %>%
  as_survey_design(weight = PANELWEIGHT, id = EAID_1, strata = STRATA_RECODE) %>%
  filter(CP_1 < 90 & CP_2 < 90) %>%
  group_by(COUNTRY, GEOCD, GEONG) %>%
  summarise(
    survey_mean(
      CP_1 * CP_2,
      vartype = "ci",
      level = 0.95,
      proportion = TRUE,
      prop_method = "logit"
    )
  )
```

```
# A tibble: 6 × 6
# Groups:   COUNTRY, GEOCD [5]
  COUNTRY                        GEOCD              GEONG         coef `_low` `_upp`
  <int+lbl>                      <int+lbl>          <int+lbl>    <dbl>  <dbl>  <dbl>
1 1 [Burkina Faso]               NA                 NA          0.188  0.164  0.214
2 2 [Congo, Democratic Republic]  1 [Kinshasa]      NA          0.320  0.288  0.353
3 2 [Congo, Democratic Republic]  2 [Kongo Central] NA          0.268  0.215  0.329
4 7 [Kenya]                      NA                 NA          0.366  0.350  0.382
5 9 [Nigeria]                    NA                  2 [Lagos] 0.293  0.259  0.330
6 9 [Nigeria]                    NA                  4 [Kano]  0.0537 0.0322 0.0880
```

1.6 INCLUSION CRITERIA FOR ANALYSIS

The remainder of this guide will feature code you can use to reproduce key indicators included in the **PMA Longitudinal Brief** for each sample. In many cases, you'll find separate reports available in English and French, and for both national and sub-national summaries. For reference, here are the highest-level population summaries available in English for each sample where Phase 2 IPUMS PMA data is currently available:

- Burkina Faso
- DRC - Kinshasa
- DRC - Kongo Central
- Kenya
- Nigeria - Kano
- Nigeria - Lagos

Panel data in these reports is limited to the *de facto* population of women who completed the Female Questionnaire in both Phase 1 and Phase 2. This includes women who slept in the household during the night before the interview for the Household Questionnaire. The *de jure* population includes women who are usual household members, but who slept elsewhere that night. We'll remove *de jure* cases recorded in the variable RESIDENT.

For example, returning to our "wide" data extract for Burkina Faso, you can see the number of women who slept in the household before the Household Questionnaire for each phase reported in `RESIDENT_1` and `RESIDENT_2`:

`NA` cases in `RESIDENT_2` represent women who were lost to follow-up in Phase 2.

```
dat %>% count(RESIDENT_1)
```

```
# A tibble: 3 × 2
  RESIDENT_1                                          n
  <int+lbl>                                       <int>
1 11 [Visitor, slept in hh last night]              106
2 21 [Usual member, did not sleep in hh last night]  174
3 22 [Usual member, slept in hh last night]         6510
```

```
dat %>% count(RESIDENT_2)
```

```
# A tibble: 5 × 2
  RESIDENT_2                                                      n
  <int+lbl>                                                   <int>
1 11 [Visitor, slept in hh last night]                           74
2 21 [Usual member, did not sleep in hh last night]             230
3 22 [Usual member, slept in hh last night]                    5993
4 31 [Slept in hh last night, no response if usually lives in hh]    1
5 NA                                                           492
```

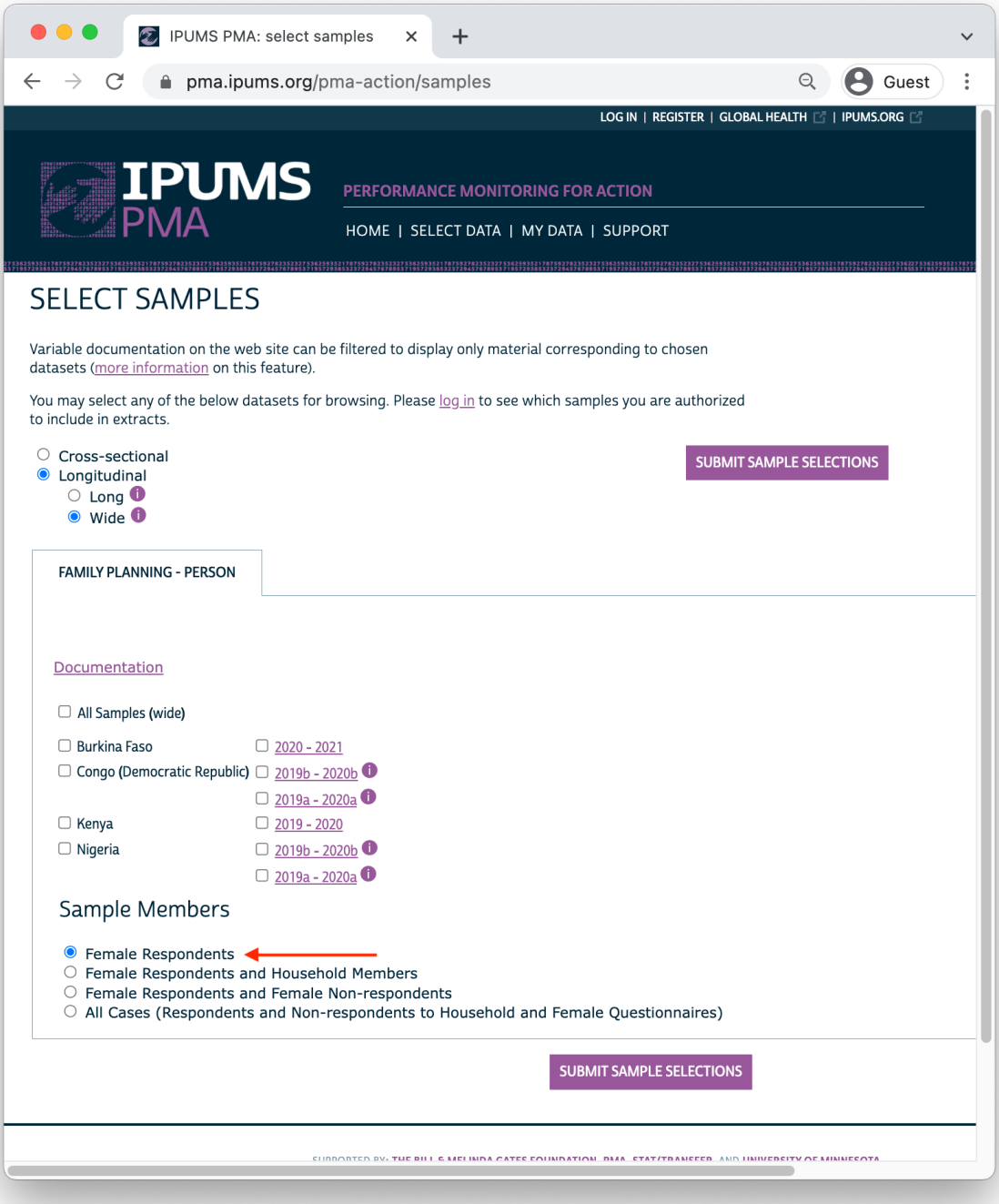
The *de facto* population is represented in codes 11 and 22. We'll use `filter` to include only those cases.

```
dat_2 <- dat %>%
  filter(
    RESIDENT_1 == 11 | RESIDENT_1 == 22,
    RESIDENT_2 == 11 | RESIDENT_2 == 22
  )

dat_2 %>% count(RESIDENT_1, RESIDENT_2)
```

```
# A tibble: 4 × 3
  RESIDENT_1                                RESIDENT_2                                   n
  <int+lbl>                                 <int+lbl>                                <int>
1 11 [Visitor, slept in hh last night]      11 [Visitor, slept in hh last night]        56
2 11 [Visitor, slept in hh last night]      22 [Usual member, slept in hh last ni…      39
3 22 [Usual member, slept in hh last night] 11 [Visitor, slept in hh last night]        17
4 22 [Usual member, slept in hh last night] 22 [Usual member, slept in hh last ni…    5855
```

Additionally, these reports only include women who completed (or partially completed) both Female Questionnaires. This information is reported in RESULTFQ. In our "wide" extract, this information appears in RESULTFQ_1 and RESULTFQ_2: if you select the "Female Respondents" option at checkout, only women who completed (or partially completed) the Phase 1 Female Questionnaire will be included in your extract.



We'll further restrict our sample by selecting only cases where RESULTFQ_2 shows that the woman also completed the Phase 2 questionnaire. Notice that, in addition to each of the value 1 through 10, there are several **non-response codes** numbered 90 through 99. You'll see similar values repeated across all IPUMS PMA variables, except that they will be left-padded to match the maximum width of a particular variable (e.g. 9999 is used for INTFQYEAR, which represents a 4-digit year for the Female Interview).

```
dat %>% count(RESULTFQ_2)
```

```
# A tibble: 11 × 2
   RESULTFQ_2                                          n
   <int+lbl>                                       <int>
 1  1 [Completed]                                  5491
 2  2 [Not at home]                                  78
 3  3 [Postponed]                                    22
 4  4 [Refused]                                      66
 5  5 [Partly completed]                             12
 6  7 [Respondent moved]                             15
 7 10 [Incapacitated]                                19
 8 95 [Not interviewed (female questionnaire)]        4
 9 96 [Not interviewed (household questionnaire)]   192
10 99 [NIU (not in universe)]                       399
11 NA                                               492
```

Possible **non-response codes** include:

- 95 Not interviewed (female questionnaire)
- 96 Not interviewed (household questionnaire)
- 97 Don't know
- 98 No response or missing
- 99 NIU (not in universe)

The value NA in an IPUMS extract indicates that a particular variable is not provided for a selected sample. In a "wide" **Longitudinal** extract, it may also signify that a particular person was not included in the data from a particular phase. Here, an NA appearing in RESULTFQ_2 indicates that a Female Respondent from Phase 1 was not found in Phase 2.

You can drop incomplete Phase 2 female responses as follows:

```
dat_3 <- dat %>% filter(RESULTFQ_2 == 1)

dat_3 %>% count(RESULTFQ_1, RESULTFQ_2)
```

```
# A tibble: 2 × 3
  RESULTFQ_1           RESULTFQ_2        n
  <int+lbl>            <int+lbl>     <int>
1 1 [Completed]        1 [Completed]  5487
2 5 [Partly completed] 1 [Completed]     4
```

Generally, we will combine both filtering steps together in a single function like so:

```
dat <- dat %>%
  filter(
    RESIDENT_1 == 11 | RESIDENT_1 == 22,
    RESIDENT_2 == 11 | RESIDENT_2 == 22,
    RESULTFQ_2 == 1
  )
```

In subsequent analyses, we'll use the remaining cases to show how PMA generates key indicators for **contraceptive use status** and **family planning intentions and outcomes**. The summary report for each country includes measures disaggregated by demographic variables like:

- MARSTAT - marital status
- EDUCATT and EDUCATTGEN - highest attended level of education[16]
- AGE - age
- WEALTHQ and WEALTHT - household wealth quintile or tertile[17]
- URBAN and SUBNATIONAL - geographic location[18]

[16] Levels in EDUCATT may vary by country; EDUCATTGEN recodes country-specific levels in four general categories.

[17] Households are divided into quintiles/tertiles relative to the distribution of an asset SCORE weighted for all sampled households. For subnationally-representative samples (DRC and Nigeria), separate wealth distributions are calculated for each sampled region.

[18] SUBNATIONAL includes subnational regions for all sampled countries; country-specific variables are also available on the household - geography page.