Advancing the Use of Service Statistics for Estimating Modern Contraceptive Use through Bayesian Modelling Approaches

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To Mam and Dad,

Thank you for your endless encouragement.

Declaration

I hereby declare that I have produced this manuscript without the prohibited assistance of any third parties and without making use of aids other than those specified.

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Abstract

Monitoring family planning progress requires accurate and timely estimates of key indicators such as the modern contraceptive prevalence rate (mCPR), defined as the proportion of women of reproductive age using modern contraceptive methods. However, large-scale survey data, often the primary source of these mCPR estimates, are infrequently collected, leading to data gaps. Family planning service statistics, routinely collected during service delivery, provide a supplementary data source. From these statistics, an indicator known as Estimated Modern Use (EMU) can be derived, but it is a biased estimator of mCPR and has uncertainties that need to be considered. This thesis focuses on advancing the methodology, application, and usability of EMU by quantifying and accounting for biases and uncertainties and ultimately better supporting low- and middle-income countries in tracking family planning progress.

First, we refine the derivation of EMU by improving upon necessary adjustments for missing private sector contributions to family planning service statistics databases. Previous methods carried out adjustments assuming constant contraceptive supply share distributions over time and without quantifying uncertainty associated with supply share estimates. We update and improve upon the EMU calculation to reflect time-varying contraceptive supply and capture uncertainty in the private sector adjustment, resulting in observation-specific uncertainty previously unseen in EMU derivation. These improvements are demonstrated through country-level case studies.

Next, we develop a new approach to incorporating EMUs into the Family Planning Estimation Tool (FPET), which generates estimates and short-term projections

of mCPR. We use a Bayesian hierarchical modelling approach to estimate data type-specific EMU uncertainty and across country variance parameters before incorporating the resulting estimates into FPET. We introduce a Bayesian hierarchical model when using EMUs in FPET to capture uncertainty, accounting for country- and type-specific uncertainties through the hierarchically estimated variance hyperparameters. Model validation results and anonymised country-level case studies highlight the impact to mCPR estimates when including EMU data in FPET using this approach. Validation findings demonstrate improved predictive performance with EMU inclusion compared to relying on survey data alone, while case studies provide further insights into its effects across different country contexts.

Finally, we present a paper to describe the details and implementation of `ss2emu`, an open-source R package, developed to perform the most advanced SS-to-EMU calculation process in R. This tool complements existing workflows performed by country-level data experts, providing reproducible datasets and visualisations for use in FPET. By offering a scalable and user-friendly solution, the tool enhances accessibility and empowers users, such as family planning monitoring and evaluation officers, to make more informed decisions in family planning monitoring.

Together, these contributions improve the accuracy, integration, and usability of EMU as a family planning indicator, enabling countries to better monitor progress toward family planning goals and address data gaps with confidence.

List of Abbreviations

Abbreviation	**Definition**
EMU	Estimated Modern Use
SS-to-EMU	Service Statistics to EMU
FPET	Family Planning Estimation Tool
mCPR	Modern Contraceptive Prevalence Rate
AWRA	All Women of Reproductive Age
MWRA	Married Women of Reproductive Age
UWRA	Unmarried Women of Reproductive Age
FP2030	Family Planning 2030
STM	Short-Term Contraceptive Method
LAPM	Long-Acting and Permanent Contraceptive Method
IUD	Intrauterine device
DHS	Demographic and Health Surveys
MICS	Multiple Indicator Cluster Surveys
TMMP	Temporal Models for Multiple Populations
UNPD	United Nations Population Division
SDG	United Nations Sustainable Development Goal
LMIC	Low- and Middle-Income Countries
EMU-clients	EMUs derived using contraceptive commodities distributed to clients' service statistics
EMU-facilities	EMUs derived using contraceptive commodities distributed to facilities' service statistics

FP visits	EMUs derived using family planning visits to facilities' service statistics
FP users	EMUs derived using family planning users at facilities' service statistics

Contents

Publications

The chapters in this thesis have been prepared for submission to peer-reviewed journals. Chapter 2 has been submitted to *Gates Open Research* and is currently under review. Chapter 3 has been submitted to *Journal of Applied Statistics*. Chapter 4 is being finalised for submission.

Submitted articles

- Mooney, S., Alkema, L., Comiskey, H., Sonneveldt, E., Bietsch, K., Williamson, J., Rosenberg, R., Reeves, M., Cahill, N. (2024). Considering the role of the private sector adjustment in calculating Estimated Modern Use from Family Planning Service Statistics. Under review in *Gates Open Research*. (https://verixiv.org/articles/2-27/v1)

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Articles in preparation

- Mooney, S., Alkema, L., Comiskey, H., Bietsch, K., Cahill, N. (2024). `ss2emu`: An R Package for Calculating Estimated Modern Contraceptive Use using Family Planning Service Statistics. In preparation to submit.

Implementation in Practice

The methods and findings from this thesis were put into practice at the Track20 Annual Monitoring and Evaluation Training in Family Planning Workshop, held in Nairobi, Kenya, in April 2024. This workshop brought together representatives from over 30 low- and middle-income countries, facilitating engagement and discussion on the use of these approaches.

This implementation continues to have a global impact, informing family planning estimation and policy decisions worldwide. The ongoing use of these methods highlights their relevance in real-world applications and their role in strengthening data-driven decision-making in family planning programs.

CHAPTER 1

Introduction

1.1 Motivation

Family planning is a crucial aspect of reproductive health and rights, which is integrated into the United Nations' Sustainable Development Goals (SDGs) (UN Committee on Economic, Social and Cultural Rights [2000], United Nations). Specifically, Target 3.7 of the SDGs urges countries to "by 2030, ensure universal access to sexual and reproductive health-care services, including for family planning, information and education" (World Health Organization). In order to achieve these goals, and inform policy, performance monitoring of key family planning indicators, particularly in low- and middle- income countries (LMICs) is crucial.

As progress is being made towards SDG targets, there is an increasing recognition that monitoring key indicators requires enhanced capacity and improved data use (Keijzer and Klingebiel [2017]). An important aspect of this is the use of diverse data sources, including administrative data and survey data. However, administrative health data in LMICs often suffer from biases and quality issues with respect to indicators of interest (Naz et al. [2023]). These include incomplete reporting, under-representation of private sector facilities, and inconsistencies in data collection methods, all of which hinder the derivation of reliable health indicators. Systematic reviews highlight gaps in the quality and management of routine health information systems at the community and district levels in LMICs, citing lack of resources in facilities as one of the many challenges faces in these settings (Ndabarora et al. [2014]). These gaps hinder data equity and pose barriers to advancing health equity in settings with limited resources (Measure Evaluation [2018], O'Neil et al. [2021]). However, some of these challenges can be addressed through the use of statistical methods that correct biases and quantify uncertainty to ensure that data-informed estimates used for decision-making are accurate and reliable.

The modern contraceptive prevalence rate (mCPR) is a key indicator for monitoring family planning progress, defined as the proportion of women of reproductive age using modern contraceptive methods, such as hormonal methods, sterilisation, barrier methods, and emergency contraception (Hubacher and Trussell [2015]). To assess progress toward family planning goals, and to support evidence-based policy development, countries need timely and reliable estimates of mCPR.

To monitor mCPR and other family planning indicators, the Family Planning Estimation Tool (FPET) was developed (Alkema et al. [2013], New et al. [2017], Cahill et al. [2018], Kantorová et al. [2020], Alkema et al. [2024c]). FPET combines a Bayesian hierarchical model with country-specific time trends to produce estimates and short-term forecasts of family planning indicators, using survey-based data as input. However, as large-scale health surveys are typically conducted on average every 3-5 years, this can lead to data gaps, resulting in projections and estimates that are not data-driven.

To address survey data gaps in FPET, family planning service statistics, a form of administrative health data which are generated as a by-product of service delivery, can be used as a supplementary data source. These service statistics are used to derive a family planning indicator known as Estimated Modern Use (EMU) (Track20 [2020]). For similar reasons outlined previously with respect to issues with administrative health data, EMU data are recognised as a biased estimate of mCPR (Magnani et al. [2018]). Despite this, studies have shown that rates of change in EMU are unbiased with respect to mCPR and can be used in FPET to inform mCPR estimates when more recent survey data are unavailable (Cahill et al.

[2018]). However, these studies did not account for observation-specific uncertainty in EMUs or consider country-specific contexts. Instead, uncertainty was assessed solely based on the EMU data type, which depends on the type of service statistics used to derive the EMUs, such as the number of family planning commodities distributed or the number of visits to family planning facilities. Evaluating EMU model uncertainty globally by data type can reduce the impact of high-quality EMU data in certain countries. This is because some EMU types inherently have greater uncertainty, and when applied at the country level, this can lead to inflated uncertainty estimates.

This thesis aims to advance the use of family planning service statistics through the derivation of EMU, including updates to uncertainty quantification in their estimation and use in FPET, and the development of an R package to facilitate their application. The methods developed will contribute to monitoring family planning progress, ultimately supporting improved health policy and decision-making in LMICs. Examples of such decision-making include interventions aimed at reducing financial barriers to contraceptive healthcare, such as family planning vouchers (Bhatia and Gorter [2007], Ali et al. [2019], Bellows et al. [2017]), implementing community health worker programs to address inequities in access caused by geographic or social barriers (Liu et al. [2011]), and initiatives designed to increase educational attainment among girls (The High Impact Practices Partnership [2022], Asiimwe et al. [2013]).

1.2 Overview of the SS-to-EMU process

Service statistics consist of four types of data: (1) the number of contraceptive commodities distributed to clients (e.g. pill packets, implants), (2) number of contraceptive commodities distributed to facilities, (3) number of family planning visits to facilities and (4) current contraceptive users registered to facilities, including those using long-acting methods from previous years. The types of service statistics collected varies across countries. This section will provide a brief overview of the process of deriving EMU from service statistics, known as the SS-to-EMU process. This process was developed by Track20, a project dedicated to collaborating with and monitoring progress of countries committed to Family Planning 2030, a global initiative focused on increasing safe access to reproductive healthcare worldwide (https://www.fp2030.org/) (Track20 [2023]).

1. **Calculate short-term method (STM) users.** Data on commodities distributed and family planning visits for short-term contraceptive methods are converted into users using Couple Years of Protection (CYP) factors, which quantify the contraceptive coverage provided by a single unit or visit of each method (U.S. Agency for International Development).

2. **Calculate long-acting and permanent method (LAPM) users.** Since LAPMs provide protection over multiple years, users must be accounted for across time. The total number of LAPM users includes new users in a given year, continuing users from previous years, and historic users whose protection extends into the current year. Method-specific continuation rates determine how many users from past years remain active (Data For Impact [a]).

3. **Adjust the number of users for missing private sector contributions.** Private sector contributions, including those from NGOs, private hospitals, clinics, pharmacies, are often under-reported or absent from service statistics (Magnani et al. [2018]). To ensure that EMUs accurately represent the entire contraceptive market and account for these contributions, a private sector adjustment is applied to service statistics. The adjustment factor is calculated using the contraceptive supply share (the proportion of each contraceptive method provided by different facility types) (Data For Impact [d]) and the representation of each facility type in the data. It is then applied to adjust the annual number of users for each contraceptive method.

4. **Calculate Estimated Modern Use.** Annual number of users of each contraceptive method are summed across all methods to provide an annual estimate of the number of modern contraceptive users. This estimate is expressed as a proportion of the population of women of reproductive age, providing Estimated Modern Use.

1.3 Relevant statistical background

In this section, we briefly discuss the statistical modelling techniques that are central to this thesis.

1.3.1 Bayesian Hierarchical Modelling

Bayesian hierarchical models are designed to handle data with hierarchical or multi-level structures (Gelman et al. [2013]). This is particularly valuable in global health indicator modelling, where data often have a natural hierarchical structure, such as data collected across countries, which can be structured at global, regional, and national levels. Hierarchical modelling enables the sharing of information across groups, improving parameter estimates, particularly in cases with sparse data, by allowing data-rich contexts to inform those with limited information.

A key advantage of Bayesian models is their ability to account for uncertainty throughout all stages of inference, distinguishing them from frequentist approaches that do not consider parameter uncertainty within the model. Bayesian hierarchical models incorporate uncertainty at multiple levels and leverage partial pooling to achieve more accurate and interpretable estimates, especially in scenarios with multiple levels of variation or limited data within subgroups.

Partial pooling is a key feature of Bayesian hierarchical models that balances individual group estimates with the global trend. Rather than treating groups completely independently (no pooling) or assuming they are the same (complete pooling), partial pooling allows group-specific estimates to "shrink" toward the global mean. The degree of shrinkage depends on the amount of data available for each group, groups with less data are shrunk more toward the global mean, whilst groups with more data have less shrinkage. This approach helps avoid overfitting and provides better predictions, especially for groups with limited information.

A typical hierarchical model includes:

- Level 1 (Individual-level): Describes variability within groups, often using regression equations for individual observations. For example:

$$y_{i,j} \sim N(\alpha_i, \sigma^2) \tag{1.1}$$

where $y_{i,j}$ is the observed outcome for the j^{th} observation within the i^{th} group, α_i is the mean for the i^{th} group and σ^2 is the variance within each group, representing the spread of individual observations around the group mean α_i.

- Level 2 (Group-level): Captures variation between groups by specifying distributions for group-specific parameters. For example:

$$\alpha_i \sim N(\alpha_\mu, \tau^2) \tag{1.2}$$

where α_i is the group-specific parameter (the mean of group i), α_μ is the overall mean of the group-specific parameters and τ^2 is the variance between groups, quantifying how much the group-specific means α_i deviate from the overall mean α.

- Higher levels (if applicable): Extends the structure to account for broader groupings, such as regions containing countries. For example:

$$\alpha_\mu \sim N(\mu, \delta^2) \tag{1.3}$$

where α_μ is the mean of all the group-specific parameters α_i from Level 2, μ is overall mean across all groups in the model and δ^2 is the variance between higher-level groups, representing how much the group-level means α_μ vary across broader categories such as regions or clusters.

Applications of Bayesian hierarchical models in global health include estimating causes of maternal deaths in data-sparse settings (Chong et al. [2024]), and estimating the population of women of reproductive age at the subnational level in data-limited contexts (Alexander and Alkema [2022]). Other applications include modelling neonatal mortality globally (Alexander and Alkema [2018]), and producing country-specific projections of the total fertility rate for all countries (Alkema et al. [2011]).

Bayesian hierarchical modelling is implemented in FPET, to provide estimates and short-term projections of family planning indicators at the country level (Alkema et al. [2013], New et al. [2017], Cahill et al. [2018], Kantorová et al. [2020], Alkema et al. [2024c]). FPET leverages a global model fit with a hierarchical structure that allows for information sharing across populations. This means that when a country's data is limited, the model borrows strength from global trends, overcoming data limitations and improving the accuracy of estimates.

In the context of this thesis, we group EMU data by country and data type, leveraging the hierarchical framework to allow data-rich contexts to inform estimates and uncertainties in sparser settings. We introduce a Bayesian hierarchical model when using EMUs in FPET to capture uncertainty, accounting for country- and type-specific uncertainties through hierarchically estimated variance hyperparameters. This analysis includes data from a total of 23 countries, using 4 service statistics data types. On average, each country collects 2 data types and there are 6 data points per country and data type. However, 6 countries have 2 data points or fewer for a given data type.

1.3.2 Temporal Models for Multiple Populations

Temporal Models for Multiple Populations (TMMPs) are a class of Bayesian statistical models designed to estimate demographic and global health indicators across multiple populations over time (Susmann et al. [2022]). These models are particularly useful when data are limited, vary in quality, or come from diverse sources, helping to produce reliable estimates and projections with uncertainty. The key component of TMMPs is the definition of the process model and the data model.

The process model captures the underlying trend of the latent indicator of interest over time, considering the systematic trend, data-driven deviations from it, and incorporates covariates when applicable. The data model defines the relationship between the observed data and the latent indicator. The data model considers multiple types of measurement error, making it well structured to combine multiple data sources. Additionally, TMMPs incorporate hierarchical modelling to share information across populations, allowing parameter estimates from data-rich populations to inform those with limited or no data.

In the context of this thesis, FPET is classed as a TMMP, using both a process model and data models to estimate and project family planning indicators, including mCPR, over time (Alkema et al. [2013], New et al. [2017], Cahill et al. [2018], Kantorová et al. [2020], Alkema et al. [2024c]). One of the data models implemented in FPET is the EMU data model. As the derivation of EMU with uncertainty and their use in FPET via the data model is a central focus of this thesis, FPET and the use of EMU data in FPET will be discussed in greater detail in Sections 1.3.3 and 1.4.

Further examples of models that can be described as TMMPs include the model described by Wang et al. [2017], which estimated all-cause mortality by age, sex, and location from 1970 to 2016, and the model by Alkema et al. [2017], which was used to estimate maternal mortality globally.

1.3.3 Family Planning Estimation Tool

The Family Planning Estimation Tool (FPET) is a Bayesian hierarchical model that produces country-level estimates and short-term forecasts of key family planning indicators, including mCPR, for married, unmarried and all women of reproductive age (Alkema et al. [2013], New et al. [2017], Cahill et al. [2018], Kantorová et al. [2020], Alkema et al. [2024c]). FPET relies primarily on survey data to inform estimates. It can combine data from multiple survey types, such as Demographic and Health Surveys (DHS), Multiple Indicator Cluster Surveys (MICS), and Performance Monitoring for Action (PMA) surveys (The DHS Program [a], UNICEF, Performance Monitoring for Action). Population data for married and unmarried women of reproductive age used to compute estimates are sourced from the United Nations Population Division (United Nations Population Division [b]).

As a TMMP, FPET combines a process model and a data model (Susmann et al. [2022]). The process model assumes that true family planning indicators, such as mCPR, follow an S-curve trajectory, with the rate of change determined by an expected rate of change plus country-year-specific deviations. The survey data model captures how survey data is assumed to relate to the true family planning indicators, accounting for various types of errors associated with the data, including sampling errors, source-type errors (due to variability across different survey types), and outlier errors, which determine whether a given observation is classified as an outlier (Alkema et al. [2024c]). When using EMU within FPET to inform estimates and projections of mCPR, the EMU data model is implemented alongside the survey data model (Cahill et al. [2021]). Section 1.4 further details the use of EMUs in FPET.

1.4 Evolution of using EMU in FPET

There have been three core iterations of the use of EMU derived from service statistics to inform mCPR estimates in FPET, each iteration aiming to use more accurate modelling assumptions based on what we know about the relationship between EMUs and mCPR and to better quantify uncertainty associated with service statistics and subsequently EMU.

First iteration: Bias adjustment

Initially, Cahill et al. [2018] introduced the use of EMUs with a bias adjustment, which involved a two-step modelling process to estimate and account for the known bias between EMU and mCPR. This required two consecutive model runs: the first run with just survey data to estimate the relative bias in the EMUs, and the second incorporated bias-adjusted EMUs to inform mCPR trends after the most recent survey. Specific criteria had to be met for service statistics to be deemed reliable for use in this process. These criteria required that service statistics be consistently reported over multiple years, with at least three years of data, including one year overlapping with a survey period. Additionally, at least one year of service statistics data had to be reported after the most recent survey to enable bias estimation.

Second iteration: Using rates of change

Following this, Cahill et al. [2021] introduced the use of EMU rates of change to inform mCPR rates of change for MWRA. This method aligned more closely with where the value lies in service statistics, capturing trends in contraceptive use (Magnani et al. [2018]). While EMUs provide a biased estimate of mCPR levels, EMU rates of change are assumed to be unbiased with respect to rates of change in the true, unknown mCPR, addressing these biases. Removing the need for a bias adjustment simplified the process, requiring only one model run, and two years of data. Additionally, the overlap with survey periods was no longer necessary.

This approach also addressed uncertainty in the EMU data model via a global, type-specific assessment of EMU uncertainty within FPET. However, this could lead to inflated uncertainty in countries where service statistics or EMUs were considered high quality. This reduced the overall impact of including service statistics on mCPR estimates in these contexts. Additionally, while service statistics are generally collected with respect to AWRA, FPET's model structure at the time meant they directly informed MWRA estimates. This approach indirectly informed AWRA, but UWRA did not benefit from the inclusion of EMUs.

Third iteration: Updates to uncertainty

The third iteration of the use of EMU data in FPET is described in this thesis. Chapter 2 introduces the latest advancements in the EMU calculation process, which quantifies observation-level uncertainty introduced during derivation (Mooney et al. [2024a]). Chapter 3 builds on the work described Chapter 2, updating the EMU data model in FPET to include observation-level uncertainty (Mooney et al. [2024a]). Specifically, this approach uses annual EMU rates of change as input and enables the decomposition of uncertainty into two components: observational-level uncertainty and country, type-specific uncertainty.

To assess EMU type-specific uncertainty at the country level, a Bayesian hierarchical modelling approach was employed. This used observed differences between rates of change in EMU and rates of change in mCPR during survey-informed years, along with observation-specific uncertainties, to directly inform our uncertainty estimates. This allowed for information sharing across service statistics types and countries. This update improved the quantification of uncertainty in the EMU data model, allowing it to better capture country-specific contexts, leading to more influence on mCPR estimates where EMUs are considered high quality.

Additionally, Mooney et al. [2024b] updated the EMU data model to more effectively capture the relationship between service statistics and the populations they represent. Previously, FPET used EMUs to inform MWRA estimates and projections of mCPR, which indirectly influenced AWRA estimates but had no impact on UWRA estimates. However, service statistics, and subsequently EMUs, generally capture AWRA. An update to FPET allowed the updated EMU data model to ensure that EMUs now inform the relevant population within each country, particularly impacting UWRA estimates and projections of mCPR in ways not seen in previous iterations (Alkema et al. [2024c]).

1.5 Thesis outline

Chapter 2 discusses the role of the private sector adjustment in calculating Estimated Modern Contraceptive Use from family planning service statistics. Prior to the calculation of EMU, a private sector adjustment is applied to service statistics to account for missing private sector contributions. This adjustment is based on two inputs: the contraceptive supply share (the proportion of each contraceptive method provided by different facility types) and the representation of these facilities in the data. Historically, these supply shares were held constant over time, and uncertainty was not accounted for in the EMU calculation process.

In Chapter 2, we improve upon these limitations and update EMU calculations to take account of time-varying supply shares and include an uncertainty assessment. We enhance the calculation of EMU by incorporating time-varying changes and uncertainty associated with an adjustment for the presence/absence of private sector facilities in the service statistics data which underlie EMU. Information about facility reporting levels and annual contraceptive supply shares are represented via probability distributions obtained using Demographic and Health Surveys (DHS) (The DHS Program [a]) and model estimates of the contraceptive supply share of the public and private supply share over time (Comiskey et al. [2023, 2024]). By using the annual supply-share distributions we can propagate uncertainty directly into the EMU calculation and capture temporal trends in private sector contributions to service statistics.

Overall, this refined approach represents a shift in how we interpret EMU, moving beyond reliance on point estimates to a more nuanced understanding that incorporates variability and uncertainty. Additionally, this work aims to enhance the use of EMU as a supplementary data source for informing estimates of modern contraceptive prevalence. This was achieved by extending our analysis to quantify uncertainty in annual EMU rates of change, a key aspect given EMU rates of change are used in FPET (Cahill et al. [2021]).

Building on the findings of Chapter 2, Chapter 3 addresses the challenge of infrequent survey data for monitoring mCPR in FPET. To address data gaps, we turn to EMU to provide insight on contraceptive trends. In this chapter, we present a new approach to using EMUs to inform mCPR estimates within FPET, accounting for both uncertainty associated with the EMU derivation process and the unexplained fluctuations in country-specific EMU series. A Bayesian hierarchical modelling approach is used to estimate this type-specific uncertainty, and across country variance parameters. We incorporate these parameters into a Bayesian hierarchical model in FPET. We demonstrate, through validation and anonymised case studies, that including EMU via our enhanced approach improves mCPR estimates compared to relying solely on survey data. This advancement supports more timely and accurate family planning monitoring, aiding countries in tracking progress toward their goals.

Chapter 4 presents `ss2emu`, an open source R package designed to calculate EMU using the most up-to-date calculation process in R, while complimenting an existing workflow performed by country-level data experts. The most recent EMU data model, as described in Chapter 3, requires EMU observation-level uncertainty estimates, which are generated through the updated EMU calculation process introduced in Chapter 2. However, the existing tools used to derive EMU using service statistics could not accommodate the computational demands of this updated process. To bridge the gap between these tools and the FPET's need for uncertainty estimates, and to enable the use of the updated EMU data model in country workshop settings, we needed a scalable, reproducible, and user-friendly solution. To meet this need, we developed the `ss2emu` R package. This R package performs the SS-to-EMU calculation in R, generates informative visualisations, and produces a reproducible database for use in FPET. The package provides a scalable and user-friendly solution that integrates with existing workflows, empowering users make more informed decisions while evaluating family planning progress.

Finally, Chapter 5 concludes the thesis with final remarks, summarising the contributions made and discussing opportunities for future work. Key achievements include advancements in EMU calculation, the enhancement of the use of EMU in FPET, and the creation of an R package to calculate EMU in a reproducible manner. These contributions aim to improve the monitoring of family planning indicators, ultimately supporting better health policy and decision-making.

CHAPTER 2

Considering the role of the private sector adjustment in calculating Estimated Modern Contraceptive Use from Family Planning Service Statistics

Abstract

Background: Modern contraceptive prevalence rate (mCPR), indicating the proportion of women of reproductive age using modern contraceptive methods, stands as a key measure of family planning progress. Accurate annual estimates of mCPR are crucial for actively monitoring progress toward family planning goals. Family planning service statistics are a routinely collected and readily available data source, gathered alongside service delivery. These statistics can be used to derive an indicator known as Estimated Modern Use (EMU), which acts as a proxy for mCPR. EMUs are used to provide insight into trends in annual contraceptive use, and are particularly valuable in cases where recent survey data is unavailable. EMUs have been developed and used by Track20, a project dedicated to collaborating with and monitoring the progress of countries' family planning goals, to produce estimates that allow countries to better monitor annual progress toward their family planning goals.

Methods: While contraceptives are distributed through both public and private sector facilities, the private sector is often partially or entirely absent from service statistics. To ensure that EMUs are fully representative, service statistics are adjusted to account for missing private sector contributions, referred to as the private sector adjustment. This private sector adjustment is based on estimates of the annual distribution of contraceptive supply for each contraceptive method by each type of family planning facility and the extent to which each facility type is represented in the data. In prior calculations of EMUs, estimates of method-specific contraceptive supplies were held constant over time and uncertainty was not assessed. In this chapter, we present updates to the calculation of EMUs to capture changes in contraceptive supply and uncertainty associated with the private share adjustment.

Results: We illustrate the approach through country-level case studies. We demonstrate that this approach effectively quantifies the uncertainty introduced by applying the private sector adjustment to reflect the full contraceptive market within service statistics. As a consequence, the resulting EMUs provide a more comprehensive representation of the information provided on contraceptive use captured in service statistics.

2.1 Introduction

Family Planning 2030 (FP2030) is a global initiative dedicated to ensuring access to safe reproductive healthcare (Family Planning 2030). A critical aspect of this initiative is the ongoing monitoring of key family planning indicators within FP2030 focus countries, which is vital for achieving FP2030's objectives. One such indicator is the modern contraceptive prevalence rate (mCPR), defined as the proportion of women aged 15 - 49 who are using modern contraceptive methods.

To generate country-level estimates and projections of family planning indicators, such as mCPR, the Family Planning Estimation Tool (FPET) was developed as part of the monitoring approach for FP2020, FP2030's predecessor initiative. This model combines Bayesian hierarchical modelling with country-specific time trends (Alkema et al. [2013], New et al. [2017], Cahill et al. [2018], Kantorová et al. [2020]). However, the reliance on infrequent large-scale national surveys, typically conducted every 3-5 years, introduces data gaps and substantial uncertainty into the model estimates.

To address these gaps, we turn to family planning service statistics, which are routine health facility data collected in conjunction with service delivery. There are four types of family planning service statistics, including the number of contraceptive commodities distributed to clients and facilities, the number of family planning visits at a facility, and the number of family planning users at a facility. Countries may collect different combinations of service statistics, ranging from one type to all four. These statistics are used to derive an indicator called Estimated Modern Use (EMU) (Track20 [2020]), which acts as a proxy for mCPR. EMU can be used to provide insight into population-level changes in contraceptive use. In FPET, EMU rates of change can serve as a supplementary data source to inform mCPR estimates where recent survey data is absent (Magnani et al. [2018], Cahill et al. [2021]).

The process of transforming service statistics into EMU (SS-to-EMU) was developed by Track20, a project dedicated to collaborating with and monitoring the progress of countries involved in the FP2030 initiative (Track20). As part of Track20's efforts to increase government capacity to use service statistics and other available data to monitor annual progress, the project has trained a cadre of skilled family planning-dedicated monitoring and evaluation (M&E) officers in FP2030 focus countries. These family planning data experts are available in-country to track program progress, and are responsible for collating, analysing, and communicating insights for reporting and decision-making. Track20 provides ongoing technical support and mentorship to these M&E Officers, including annual M&E training workshops where tools like SS-to-EMU are introduced, and innovative data solutions can be exchanged between countries.

The SS-to-EMU tool, which is hosted in Microsoft Excel, was created by Track20 to help countries review their service statistics and convert this data into EMU for bench-marking with mCPR derived from surveys (Track20 [2023]). M&E officers use the SS-to-EMU tool to collate service statistics and perform standardised data quality review. This tool represents a significant step towards more accurate and timely monitoring of family planning practices, ultimately contributing to the success of the FP2030 initiative.

Family planning services are provided by a variety of facilities, including government health facilities, home/community delivery services, non-governmental organisations (NGOs), private hospitals and clinics, pharmacies, and other sources. These facilities are categorised into two main sectors: the public sector, which includes government health facilities and home/community delivery services, and the private sector, which encompasses NGOs, private hospitals/clinics, pharmacies, and other non-public sources. While the public and private sectors are both key sources of family planning services (Bradley and Shiras [2022], Campbell et al. [2015]), private sector facilities are often only partially represented or completely absent from service statistics. As a result, a crucial step in the SS-to-EMU process is the private sector adjustment, through which service statistics data are scaled up to account for missing private sector facilities. The adjustment ensures that the EMU reflects contributions from both public and private sector facilities to family planning.

To adjust service statistics data for partially or fully missing private sector facilities, the SS-to-EMU calculation includes a scale-up based on a "private sector adjustment factor" developed by Track20. The adjustment factor is based on two key pieces of information: the proportion of each contraceptive method supplied by different types of facilities, known as contraceptive supply share, and the extent to which these facilities are represented in the data. By applying this adjustment factor, a scaled-up estimate of modern contraceptive users is obtained. This estimate is then used as a proportion of women of reproductive age to calculate EMU.

This chapter proposes an updated approach to calculating the private sector adjustment. Previously, the method-specific contraceptive supply share was assumed to be constant over time, and uncertainty was not assessed. Additionally, facilities deemed to be partially reporting were fixed at 50% representation. This resulted in a method-specific private sector adjustment factor that was fixed over time, with no associated uncertainty. In the updated approach, we propose the use of estimates of contraceptive supply share that vary over time, along with corresponding uncertainty estimates. In addition, we introduce a probability density function to consider some uncertainty around the estimated contribution of partially represented facilities.

The remainder of this chapter is organised as follows: we begin by presenting the relevant data and definitions. We then outline the current approach to the SS-to-EMU calculation, followed by a description of our updated methodology. This methodology is illustrated through anonymised country case studies, and we conclude with a discussion of the updated approach.

2.2 Data and Definitions

2.2.1 Modern Contraceptive Prevalence Rate

Modern contraceptive prevalence rate (mCPR) indicates the proportion of women of reproductive age using modern contraceptive methods. Modern methods of contraception include oral contraceptive pills, injectables, implants, intrauterine devices (IUD), male and female sterilization, Standard Days Method (SDM), vaginal barriers, spermicides, condoms, emergency contraception and other modern methods (The DHS Program [b]).

2.2.2 Long and Short-Term Contraceptive Methods

Contraceptive methods are categorised into two main categories: short-terms methods (STMs), and long-acting and permanent methods (LAPMs). STM provide contraceptive protection for a limited period of time, typically less than a year. While a woman may continue using a method beyond this period, a single commodity offers protection against pregnancy for only a short duration. STMs include oral contraceptive pills, injectables, lactation amenorrhea method, Standard Days Method, vaginal barriers, spermicides, condoms and emergency contraception. LAPMs include intrauterine devices (IUD), implants, female sterilization, and vasectomy (U.S. Agency for International Development [2006], Data For Impact [b]).

IUD and implants are long-acting temporary methods, whilst female sterilization and vasectomy are permanent methods.

2.2.3 Method Mix

Method mix describes the distribution of contraceptive methods within a specific population, indicating the proportion of individuals using each method (Data For Impact [c]). This measure can provide insight into the variety of contraceptive methods available in a country and their subsequent uptake. It is often used as a proxy to assess contraceptive choice and accessibility (Bertrand et al. [2014]). Data sources for method mix include national surveys and service statistics.

2.2.4 Source of Contraceptive Supply

Data on the source of contraceptive supply is derived from surveys in which women are interviewed to report the type of facility and the sector (public/private/other) from which they obtain their contraceptive methods (Data For Impact [d]). The facility categories include:

- Government health facilities.
- Home/community delivery services.
- Non-governmental organizations (NGOs).
- Private hospitals/clinics.
- Pharmacies.
- Shops/churches/friends.
- Other sources.

The public medical sector encompasses government health facilities and home/-community delivery services. The private medical sector includes NGOs, private hospitals/clinics, and pharmacies. The “other” private sector comprises shops, churches, friends, and other sources.

2.2.4.1 Data on contraceptive supply shares from Demographic and Health Surveys

Data on the source of supply for each contraceptive method is collected through Demographic and Health Surveys (DHS), which are typically conducted about every 5 years (The DHS Program [a]). This data includes two categories: the sector (public/private/other) and the type of facility where a contraceptive method was sourced. This provides observations of the proportion of each contraceptive method supplied by each type of facility providing family planning services.

2.2.4.2 Model Estimates of the contraceptive supply share

Due to the intermittent nature of DHS surveys, data on supply shares is typically not available for all country-years of interest. Model-based estimates of the shares have been produced by Comiskey et al. who use DHS data on source of contraceptive supply and employ a Bayesian hierarchical model with penalized spline functions to estimate the proportion of modern contraceptives supplied by the public and private sectors. This model yields annual, country-specific estimates of public and private sector contraceptive supply share with associated uncertainty (Comiskey et al. [2024, 2023]). This method accounts for errors in survey observations, facilitates cross-country information sharing and generates probabilistic projections based on historical data. Crucially, for this work, this approach provides insight into supply share uncertainty over time, which is significant when considering the role in the EMU calculations, particularly when there's a reliance on DHS data with no recent survey.

2.2.5 Service Statistics data types

There are four types of family planning service statistics:

1. Number of contraceptive commodities, for example pill packets and intrauterine devices, distributed to clients.

2. Number of contraceptive commodities distributed to facilities.

3. Number of times clients interacted with a provider for contraceptive services (family planning visits).

4. Number of current contraceptive users of any method including those who are still using longer acting methods that were received in previous years (family planning users).

These data are collected at the facility level and aggregated at the national level. M&E officers input the aggregated data on commodities, visits, or users into the SS-to-EMU tool. This process enables countries to review their service statistics data, and convert them into EMU. Countries collect varying combinations of these service statistics types. Service statistics data used in this chapter came from the Track20 2023 round of annual M&E training workshop.

2.3 Methodology

2.3.1 SS-to-EMU calculations

The process of transforming service statistics into EMU involves several steps. Figure 2.1 provides an overview of the SS-to-EMU process, which can be summarised in four calculation steps. Firstly, for short-term methods, commodities or visits data are standardised to reflect the number of users using Couple-Years of Protection (CYP) factors (U.S. Agency for International Development, The RESPOND Project [2011]). CYP factors quantify the duration of contraceptive protection provided by a commodity/visit.

For long-term methods, both historical users (women who obtained an LAPM before data collection began) and continuing users (women who obtained an LAPM during the data collection period, and should be considered as a user in subsequent years due to extended coverage) are estimated using contraceptive continuation rates (Data For Impact [a]). This provides initial estimates of the annual number of users of each modern contraceptive method captured by the given service statistics type. For further details on estimating the annual number of users for each contraceptive method, please refer to Appendix A.

Service statistics are typically representative of the contraceptives supplied by the public medical sector. However, given that a portion of family planning services are supplied by private sector facilities, service statistics require a scale-up adjustment to account for the private-sector supply share, in order to represent the total family planning market. This adjustment is referred to as the "private sector adjustment".

The adjustment involves a scaling factor known as the private sector adjustment factor, which adjusts the annual number of users for each contraceptive method. The calculation of this factor requires two key components. The first component is data on the reporting levels of each type of facility in the service statistics. This data categorises facilities as fully represented, partially represented, or completely absent from reporting, offering clarity on which facilities may be underrepresented or missing from the data. The second component is estimates of contraceptive supply share which detail the proportion of each contraceptive method supplied by each type of family planning facility annually. For service statistics, government health facilities and home/community delivery services are aggregated under the public medical sector, while all other facilities are considered individually.

The number of users of each method in a given year is adjusted to reflect the entire contraceptive market supply by applying the private sector adjustment factor. In country c, using service statistics type s, at time t, for contraceptive method m, we calculate a scaled-up estimate of the number of users, denoted as $\eta_{c,s,t,m}$. This estimate is derived by applying the private sector adjustment factor $\lambda_{c,s,m}$ to the annual number of users $\theta_{c,s,t,m}$, as shown in the following equation:

$$\eta_{c,s,t,m} = \lambda_{c,s,m}\theta_{c,s,t,m}. \tag{2.1}$$

The expression for the private sector adjustment factor is as follows:

$$\lambda_{c,s,m} = \frac{1}{\sum_{f=1}^{F} \tau_{c,s,f}\beta_{c,t^*,m,f}}, \tag{2.2}$$

where $\tau_{c,s,f}$ represents the facility reporting level factor, quantifying the proportion of the contribution from facility type f to service statistics type s in country c. This factor takes the value 1 if the facility type is fully reporting into the data, 0 if it is not reporting at all, and 0.5 if facilities of this type are partially reporting.

The term $\beta_{c,t^*,m,f}$ denotes the contraceptive supply share estimate for method m provided by facility f in country c, at time t^*, where t^* refers to the year of the most recent DHS observation. The resulting private sector adjustment factor is held constant over time until a newer DHS becomes available.

The EMU is calculated as the annual sum of the adjusted numbers of users across all contraceptive methods, as a proportion of the annual population of women of reproductive age. Population data is sourced from the United Nations Population Division (United Nations Population Division [a]). Let $z_{c,s,t}$ denote the EMU for country c, based on service statistics s, at time t, M represent the total number of contraceptive methods and $q_{c,t}$ represent the population of women of reproductive age in country c at time t. Typically, $q_{c,t}$ includes all women of reproductive age, but in countries where family planning data is limited to married women, $q_{c,t}$ refers to the population of married women of reproductive age. EMU is then given by:

$$z_{c,s,t} = \frac{\sum_{m=1}^{M} \eta_{c,s,t,m}}{q_{c,t}}. \tag{2.3}$$

Preserving point estimates is a key aspect of this work due to limitations with including uncertainty directly into the SS-to-EMU Excel tool. The tool has been well established in countries as the method for reviewing service statistics and moving away from using it at this point in time is counterproductive. Therefore our enhanced private sector adjustment is implemented as a post processing procedure that quantifies EMU uncertainty but ensures point estimates remain consistent with the SS-to-EMU tool output. The following sections will detail the proposed enhancements to the private sector adjustment process and subsequent improvements to the EMU calculation.

2.3.2 Updates in the EMU calculation process

2.3.2.1 Calculating EMU with uncertainty based on the private sector adjustment factor

The private sector adjustment factor varies with time and is subject to quantifiable uncertainty due to its inputs. To capture the uncertainty associated with these inputs, i.e. reporting levels and supply shares, we model them using probability

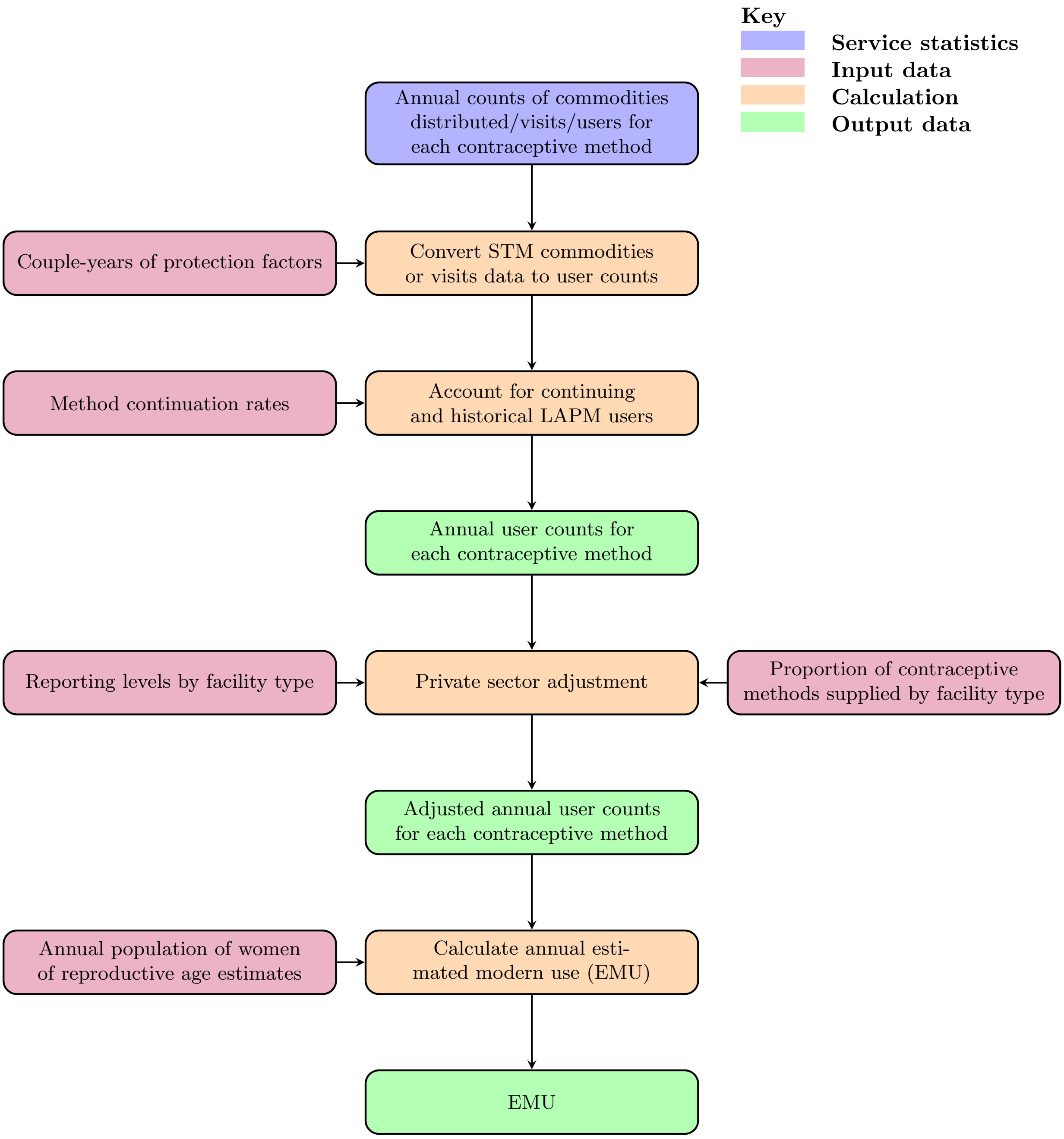


Figure 2.1: Flowchart of the process of calculating Estimated Modern Use (EMU) from service statistics. The purple box represents service statistics, while red boxes highlight the input data. The orange boxes denote the calculations performed, and green boxes indicate the resulting output data from each calculation.

densities. In the following section, we present probability densities that represent our state of knowledge of the inputs to the private adjustment factor. We use a Monte Carlo approximation, a sampling-based approach, to assess the uncertainty in the private share adjustment based on the uncertainty in its inputs. In addition, we assess how the supply shares vary with time. We update the EMU calculation accordingly, to propagate uncertainty and capture time trends in the private share adjustment.

The updated EMU calculation builds upon the calculation described in Equation 2.1. The j^{th} sample of the adjusted number of users, denoted as $\eta_{c,s,t,m,j}$, is calculated as:

$$\eta_{c,s,t,m,j} = \lambda_{c,s,t,m,j}\theta_{c,s,t,m}, \tag{2.4}$$

where $\theta_{c,s,t,m}$ is as defined in Equation 2.1. The updated expression for the j^{th} sample of the private adjustment at time t, denoted as $\lambda_{c,s,t,m,j}$, is calculated as follows:

$$\lambda_{c,s,t,m,j} = \frac{1}{\sum_{f=1}^{F} \tau_{c,s,f,j}\beta_{c,t,m,f,j}}. \tag{2.5}$$

where $\tau_{c,s,f,j}$ represent the j^{th} sample of the facility reporting level factor, which quantifies the level of contribution of facility type f in country c, in service statistics type s and $\beta_{c,t,m,f,j}$ refers to the j^{th} sample of contraceptive supply share in country c, for method m, at facility f, captured by service statistics type s. The following sections will detail how we obtain $\tau_{c,s,f,j}$ and $\beta_{c,t,m,f,j}$.

We extend Equation 2.3 to calculate EMU samples (denoted $z_{c,s,t,j}$) using samples of the adjusted number of users, alongside population estimates of women of reproductive age, such that in country c, at time t, for service statistics type s:

$$z_{c,s,t,j} = \frac{\sum_{m=1}^{M} \eta_{c,s,t,m,j}}{q_{c,t}}, \tag{2.6}$$

where M represents the total number of contraceptive methods and the denominator $q_{c,t}$ represents the population of women of reproductive age. Each EMU is summarised using the country (c), type (s), and year (t) specific median of $z_{c,s,t,1:J}$ as the point estimate. The uncertainty in the estimates is quantified using the corresponding standard deviation of the samples.

The following section will discuss the estimation of the private sector adjustment factor ($\lambda_{c,s,t,m,j}$).

2.3.2.2 Facility reporting level factors $\tau_{c,s,f,j}$

To accurately reflect the contribution of each type of facility into service statistics, three facility reporting level factors are used: 0, 1, or 0.5, representing non-reporting, full reporting, or partial reporting, respectively. In addition, we propose a more nuanced approach for facilities classified as partially reporting by sampling contributions from a Normal probability density function centered on 0.5 (truncated between 0 and 1), rather than solely relying on a fixed estimate of 0.5 in calculations. This method acknowledges the inherent uncertainty in estimating the reporting proportion for partially reporting facilities. For facilities classified as non-reporting or fully reporting, samples are consistently set to 0 or 1, respectively. Let $\tau_{c,s,f,j}$, as defined previously in Equation 2.5, be expressed as:

$$\tau_{c,s,f,j} = \begin{cases} 0 & \text{if facility } f \text{ is not reporting,} \\ 1 & \text{if facility } f \text{ is fully reporting,} \\ \sim \mathrm{N}_{[0,1]}(0.5, 0.1^2) & \text{if facility } f \text{ is partially reporting.} \end{cases} \tag{2.7}$$

2.3.2.3 Contraceptive supply share $\beta_{c,t,m,f,j}$

The private sector adjustment factor relies on contraceptive supply share estimates across seven facility categories, as defined in Section 2.2.4, with each facility category belonging to one of three sectors: public, private, or other. To address the gaps between survey data, we use linear interpolation to estimate the annual contraceptive supply share by facility category. This provides annual point estimates of contraceptive supply shares by category that capture changes over time. However, to evaluate uncertainty, we only have available model-based estimates of contraceptive supply share by sector (public/private/other) rather than by facility category. To produce uncertainty assessments that are aligned with our point estimates by facility category, we analyse uncertainty at the aggregated sector-level and then transform the estimates with uncertainty back to the original facility categories for use in the private sector adjustment calculation. Figure 2.2 illustrates an overview of this process.

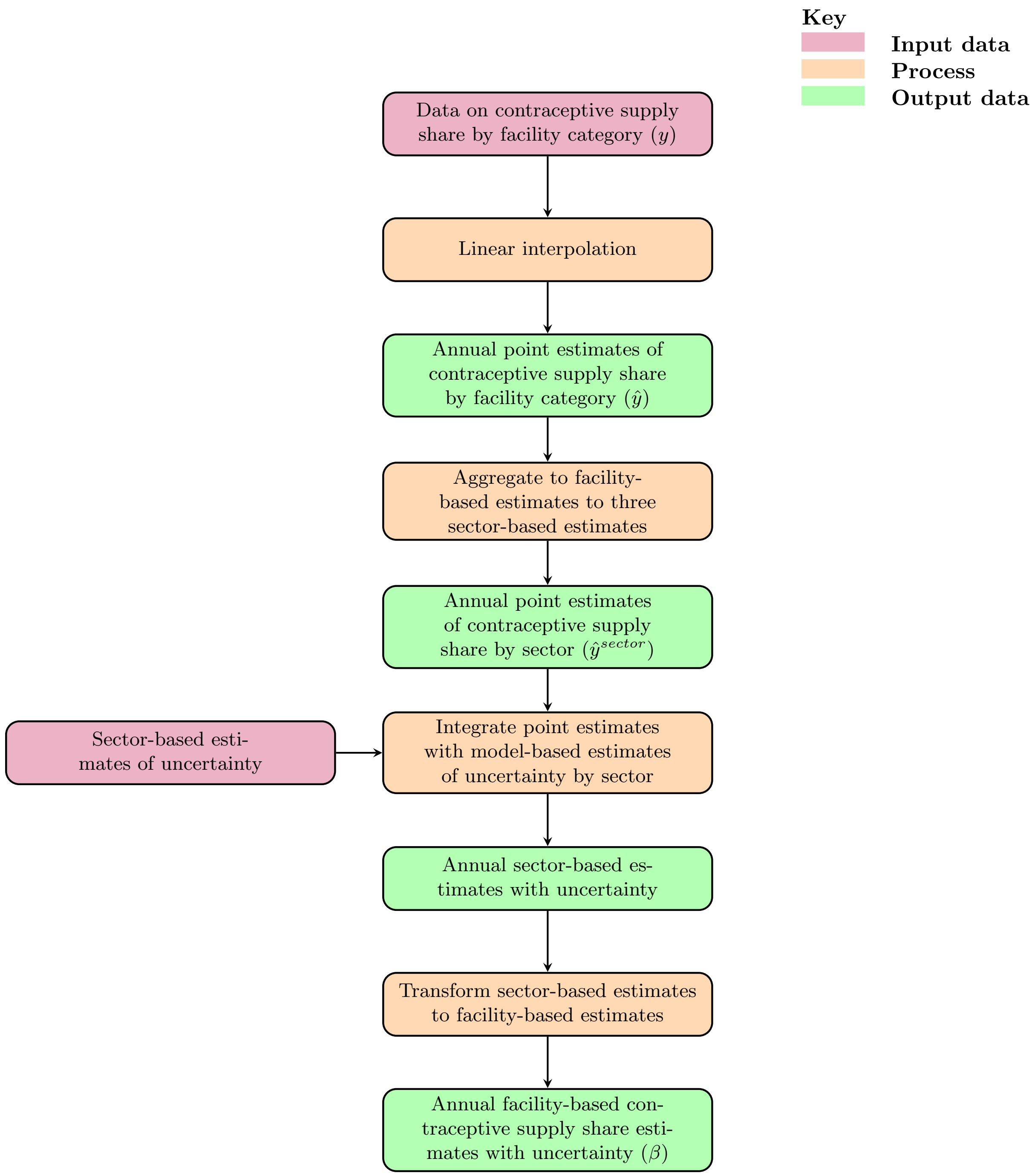


Figure 2.2: This flowchart illustrates the process of obtaining annual estimates of contraceptive supply share, including associated uncertainties, categorised by facility type. The red boxes indicate the input data sources, which consist of survey observations of contraceptive supply shares by facility category and sector-based estimates of uncertainty. Orange boxes highlight each process, while green boxes represent the outputs produced at each stage. The final output includes the annual contraceptive supply share estimates along with their uncertainties by facility, for use in the calculation of the private sector adjustment factor.

Estimating annual contraceptive supply share by facility category

We employ linear interpolation to estimate the annual contraceptive supply share between survey data points, ensuring annual estimates accurately reflect changes in contraceptive supply share over time. For a given country c, contraceptive method m, and facility type f, the annual supply share at time t, denoted by $\hat{y}_{c,t,m,f}$, is calculated using a sequence of n survey observations $(t_1, y_1), (t_2, y_2), \dots, (t_n, y_n)$, where $t_1 < t_2 < \cdots < t_n$ represent the survey years, and $y_1 = y_{c,1,m,f}, y_2 = y_{c,2,m,f}, \dots, y_n = y_{c,n,m,f}$ are the corresponding survey observations of contraceptive supply share. The estimated annual supply share $\hat{y}_{c,t,m,f}$ is computed as follows:

$$\hat{y}_{c,t,m,f} = \begin{cases} y_{c,1,m,f} & \text{if } t < t_1, \\ y_{c,i,m,f} & \text{if } t = t_i \text{ for some } i \in \{1, 2, \dots, n\}, \\ y_{c,1,m,f} + \frac{(y_{c,2,m,f} - y_{c,1,m,f})}{(t_2 - t_1)} \cdot (t - t_1) & \text{for } t_1 < t < t_2, \\ y_{c,2,m,f} + \frac{(y_{c,3,m,f} - y_{c,2,m,f})}{(t_3 - t_2)} \cdot (t - t_2) & \text{for } t_2 < t < t_3, \\ \vdots & \vdots \\ y_{c,n-1,m,f} + \frac{(y_{c,n,m,f} - y_{c,n-1,m,f})}{(t_n - t_{n-1})} \cdot (t - t_{n-1}) & \text{for } t_{n-1} < t < t_n, \\ y_{c,n,m,f} & \text{if } t > t_n. \end{cases}$$

In this approach:

- If t is before the first survey year ($t < t_1$), the supply share is assumed to remain constant at the earliest observed value $y_{c,1,m,f}$.
- If t is a survey year ($t = t_i$ for some $i \in \{1, 2, \dots, n\}$), the supply share is set to the survey observation in that year.
- If t falls between two survey years ($t_1 \leq t < t_2$), the supply share is interpolated linearly between the values observed at t_1 and t_2.
- If t is after the last survey year ($t > t_n$), the supply share is assumed to remain constant at the latest observed value $y_{c,n,m,f}$.

Modelling sector-based supply share with uncertainty

Comiskey et al. modelled country-level annual estimates of the contraceptive supply share with uncertainty across public and private sectors over time (Comiskey et al. [2024]). The model uses a compositional vector as the outcome of interest: $\phi_{c,t,m} = (\phi_{c,t,m,1}, \phi_{c,t,m,2}, \phi_{c,t,m,3})$, where $\phi_{c,t,m,1}$ represents the proportion supplied by the public medical sector, $\phi_{c,t,m,2}$ represents the proportion supplied by the private medical sector, and $\phi_{c,t,m,3}$ represents the proportion supplied by the other private sector. The model approach, which uses a process model and a data model, falls under a class of models defined as temporal models for multiple populations (TMMP) (Susmann et al. [2022]).

The process model captures the underlying trends in these proportions, using a Bayesian hierarchical penalized spline approach to model the logit-transformed proportion of the public-sector supply share ($\text{logit}(\phi_{c,t,m,1})$) and the ratio of private medical supply to the non-public sector ($\text{logit}(\frac{\phi_{c,t,m,2}}{1-\phi_{c,t,m,1}})$) (which can also be expressed as $\log(\frac{\phi_{c,t,m,2}}{\phi_{c,t,m,3}})$). The data model links these logit-transformed proportions to the observed DHS data through a Multivariate Normal distribution. The results include samples from the posterior distributions for $\text{logit}(\phi_{c,t,m,1})$ and $\text{logit}(\frac{\phi_{c,t,m,2}}{1-\phi_{c,t,m,1}})$. We summarise the uncertainty associated with $\text{logit}(\phi_{c,t,m,1})$ and $\text{logit}(\frac{\phi_{c,t,m,2}}{1-\phi_{c,t,m,1}})$ using standard deviations of the posterior samples, denoted as $\sigma_{c,t,m,1}$ and $\sigma_{c,t,m,2}$, respectively.

Converting facility-based estimates to sector-based estimates with uncertainty

We transform our annual estimates on supply share by facility category ($\hat{y}_{c,t,m,f}$) to produce sector-based estimates, to then assess the uncertainty in those estimates. The result is a set of samples, $\phi^*_{c,t,m,d,j}$, representing the j^{th} sample of the supply share proportion for method m in country c at time t, where $d = 1$ refers to the public sector, $d = 2$ to the private sector, and $d = 3$ to other private supply sources.

Let $\hat{y}^{sector}_{c,t,m,d}$ denote the proportion of contraceptives in country c, at time t, for method m, supplied by sector d. Here, d is assigned as follows: $d = 1$ for public facilities, $d = 2$ for private facilities, and $d = 3$ for facilities categorised as other.

We calculate $\hat{y}^{sector}_{c,t,m,d}$ by aggregating the annual estimates $y_{c,t,m,f}$ across all facilities f within sector d, as follows:

$$\hat{y}^{sector}_{c,t,m,d} = \sum_{f \text{ such that } d[f]=d} \hat{y}_{c,t,m,f}. \tag{2.8}$$

To integrate our point estimates of contraceptive supply share by sector ($\hat{y}^{sector}_{c,t,m,d}$), with our uncertainty estimates ($\sigma_{c,t,m,1}$ and $\sigma_{c,t,m,2}$), we adapt the structure of the previously described model approach. We represent the outcome of interest as the compositional vector $\phi^*_{c,t,m} = (\phi^*_{c,t,m,1}, \phi^*_{c,t,m,2}, \phi^*_{c,t,m,3})$, where each component reflects the proportion of supply from different sectors: $\phi^*_{c,t,m,1}$ for the public medical sector, $\phi^*_{c,t,m,2}$ for the private medical sector, and $\phi^*_{c,t,m,3}$ for the other private sector.

We first sample the public medical sector's supply proportion for method m in country c at time t on the logit scale, denoted as $\alpha_{c,t,m,1}$:

$$\alpha_{c,t,m,1} \sim \mathrm{N}(\mathrm{logit}(\hat{y}^{sector}_{c,t,m,1}), \sigma^2_{c,t,m,1}), \tag{2.9}$$

where $\hat{y}^{sector}_{c,t,m,1}$ is the estimated proportion of the public sector supply and $\sigma_{c,t,m,1}$ is the variance derived from model-based posterior output.

Similarly, the logit-transformed ratio of private sector supply to the non-public sector supply, $\alpha_{c,t,m,2}$, is sampled as:

$$\alpha_{c,t,m,2} \sim \mathrm{N}\left(\mathrm{logit}\left(\frac{\hat{y}^{sector}_{c,t,m,2}}{1-\hat{y}^{sector}_{c,t,m,1}}\right), \sigma^2_{c,t,m,2}\right), \tag{2.10}$$

where $\hat{y}^{sector}_{c,t,m,2}$ represents the estimate of the private sector supply proportion and $\sigma_{c,t,m,2}$ captures the variation in logit-transformed ratio derived from model-based posterior output.

The sample proportions on the original scale are obtained as follows:

$$\phi^*_{c,t,m,1,j} = \mathrm{logit}^{-1}(\alpha_{c,t,m,1,j}), \tag{2.11}$$

$$\phi^*_{c,t,m,2,j} = (1-\phi^*_{c,t,m,1,j})\mathrm{logit}^{-1}(\alpha_{c,t,m,2,j}), \tag{2.12}$$

$$\phi^*_{c,t,m,3,j} = 1-(\phi^*_{c,t,m,1,j}+\phi^*_{c,t,m,2,j}), \tag{2.13}$$

where $\phi^*_{c,t,m,d,j}$ represents the j^{th} sample of the supply share proportion for method m in country c at time t. Here, $d=1$ indicates public sector, $d=2$ indicates the private medical sector, and $d=3$ indicates other private supply sources. This back-transformation ensures that the proportions sum to 1 on the original scale.

Transforming sector-based estimates with uncertainty to original facility breakdown

For integration into the EMU calculation, we transform the sector-based estimates back to the facility supply shares. Let $\beta_{c,t,m,f,j}$ refer to the j^{th} sample of supply share in country c, for method m, at facility f, captured by service statistics type s. Here, $y_{c,t,m,f}$ represents the estimated proportion of the supply share at facility f in country c for method m at time t, while $\hat{y}^{sector}_{c,t,m,d}$ represents the supply share estimate of sector d in which facility f is categorised. For facilities categorised as public, $d = 1$; private, $d = 2$; and other, $d = 3$, the transformation is defined as:

$$\beta_{c,t,m,f,j} = \frac{\hat{y}_{c,t,m,f}}{\hat{y}^{sector}_{c,t,m,d}} \phi^*_{c,t,m,d,j}. \tag{2.14}$$

2.4 Results: Case Studies

This section will discuss resulting EMUs from the proposed SS-to-EMU process. We have chosen two case studies to illustrate the impact of this methodology on EMU results, referred to as Country 1 and 2 to retain data privacy. In Country 1, we consider family planning visits service statistics, whilst in Country 2, we consider contraceptive commodities distributed to clients.

2.4.1 Case Study: Country 1

We consider family planning visits service statistics type for Country 1. Figure 2.3 indicates the method mix captured by family planning visits, showing the proportion of users for each contraceptive method from 2014 to 2022. Implants and IUD consistently emerge as the most commonly used methods. Implant usage increased notably from 34.5% in 2014 to 73.6% in 2022, surpassing IUD usage in 2015. The proportion of IUD users decreased from 58.2% in 2014 to 23.4% in 2017 but remains stable thereafter. Other methods, such as injectables, pills, and female condoms, account for a smaller proportion of users, showing slight variations but remaining relatively low. Female and male sterilization, emergency contraception and other modern methods are minimally represented.

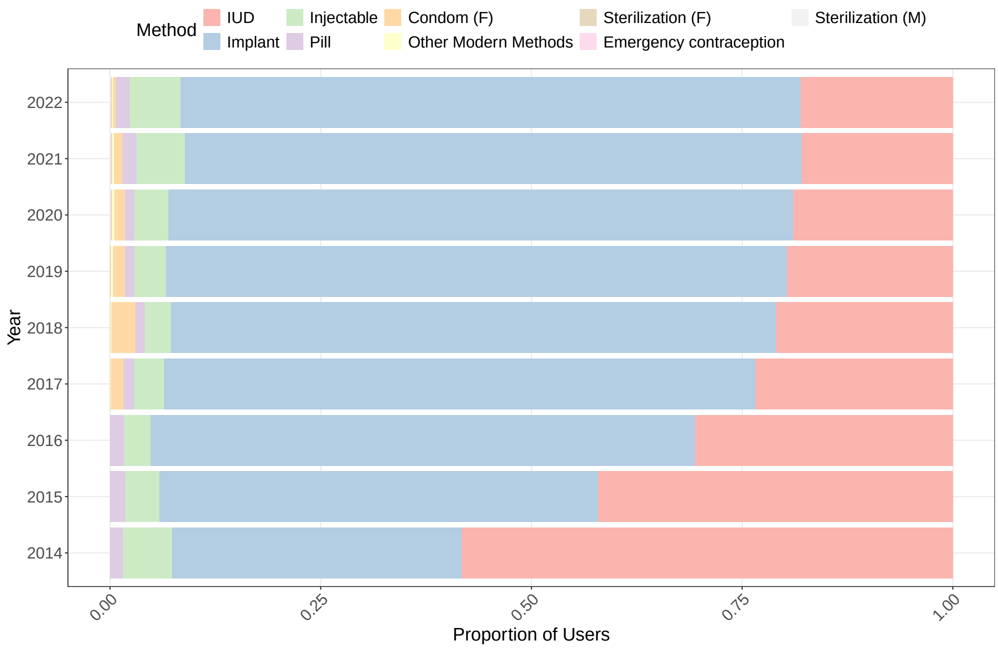


Figure 2.3: This stacked bar chart illustrates the proportion of users by contraceptive method captured in family planning visits data in Country 1 from 2014 to 2022, prior to the private sector adjustment. The methods listed are described at the beginning of the chapter. The 'pill' refers to the oral contraceptive pill and 'sterilization (F/M)' is female/male sterilization respectively. Each bar represents a year, showing the distribution of users across different methods. The colours correspond to each contraceptive method, allowing for a visual comparison of trends in usage over the years.

Figure 2.4 displays estimates and projections of the proportion of contraceptives supplied by each facility (public medical sector, NGO, pharmacies, private hospitals/clinic delivery, shop/church/friend, other) over time for implants, injectables, IUD, oral contraceptive pills and female sterilization in Country 1, spanning from 2000 to 2025. Estimates are centered on linear interpolated estimates between DHS survey observations. The data indicates that all contraceptive methods, with the exception of the oral contraceptive pill, are primarily supplied by the public medical sector. The distribution of female sterilization supply has stayed consistent over time. Generally, the other sector (other and shop/church/friend) tends to have the lowest portion of contraceptive supply share for all contraceptive methods. In terms of the private sector (NGO, pharmacies, private hospitals/clinic delivery), survey observations reveal that private hospitals/clinic delivery are the primary source of supply for all contraceptive methods, with the exception of oral contraceptive pills. Oral contraceptive pills have been primarily supplied by pharmacies since approximately 2012. The facility supply gives insight into the type of service delivery required for each contraceptive method, for example, the plot indicates that oral contraceptive pills are the only contraceptive method with a considerable proportion supplied by pharmacies. Implants, injectables, IUD and sterilization are primarily supplied by private hospitals/clinic delivery within the private sector, due to the nature of the administration of these contraceptive methods. The figure highlights the increase in uncertainty in the supply share as time since the most recent survey increases.

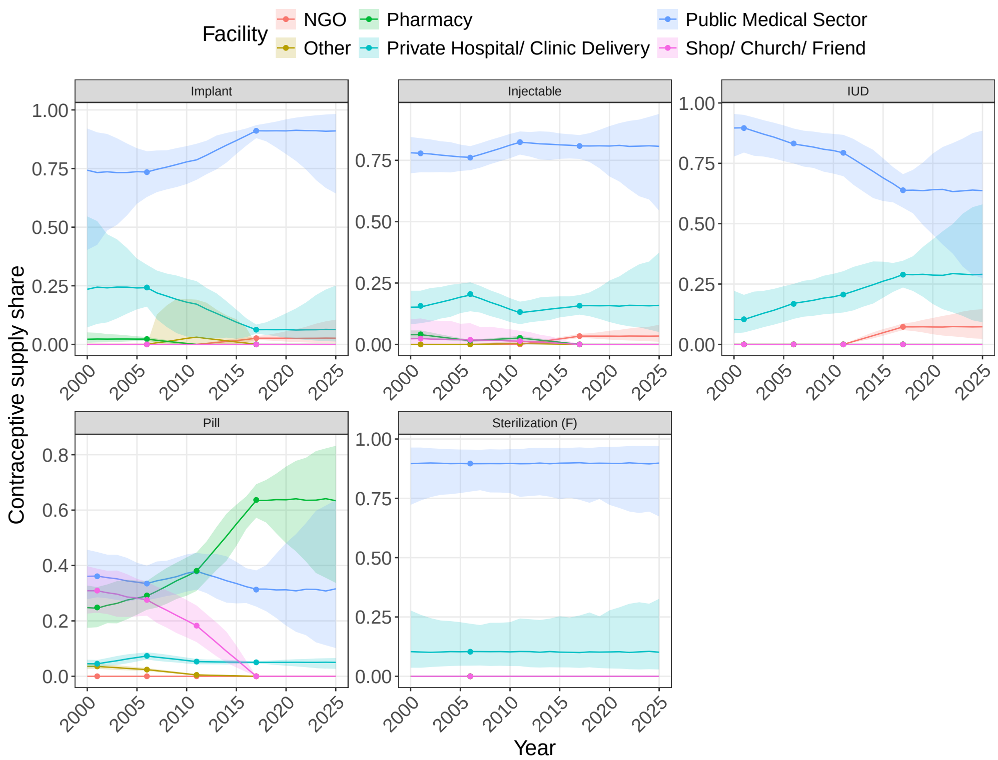


Figure 2.4: This plot illustrates estimates and projections of contraceptive supply share by facility type over time in Country 1, categorised by contraceptive method. The x-axis represents the years from 2005 to 2025, while the y-axis shows the contraceptive supply share ranging from 0 to 1. Different colors indicate various facility types. The solid line represents the median estimate, while the shaded areas depict the 95% credible interval. Points correspond to survey observations.

Table 2.1 summarises user inputted data capturing which facilities are represented in the family planning visits data. In summary, the public sector is fully represented in the data, whilst for the private sector, NGOs and private hospitals/clinic delivery are partially present, and pharmacies are not present in the data. None of the facilities within the other sector are reported in the data. This information, combined with the proportion of contraceptives supplied by each facility for each contraceptive method (Figure 2.4) are used to calculate the private sector adjustment factor over time for Country 1, for each contraceptive method.

Sector	**Facility**	**Reporting**
Public	Public Health Facilities and Community Health Services	Yes
Private	Non-Governmental Organisations (NGO)	Partially
Private	Private Hospital/Clinic Delivery	Partially
Private	Pharmacy	No
Other	Shop/Church/Friend	No
Other	Other	No

Table 2.1: This table summarises the reporting status of each facility type within different sectors: public, private, and other, in Country 1. The reporting levels are categorised as follows: "Yes" indicates that the facility type is fully represented in service statistics; "Partially" indicates partial representation; and "No" indicates absence from the data. This information is essential for adjusting for missing facilities during the private sector adjustment process and is a key component in calculating the private sector adjustment factor.

Figure 2.5 illustrates the resulting private sector adjustment over time for each contraceptive method in Country 1 for family planning visits data, spanning from 2000 to 2025. The uncertainty of the facility contraceptive supply shares and partially reporting facilities directly influences the uncertainty of the private sector adjustment factor for each contraceptive method. Where the median facility supply share estimate was fixed past the most recent survey, the median private sector adjustment factor is fixed going forward in time. With respect to implants, for example, the median private sector adjustment factor is fixed from 2017, corresponding to the year of the most recent supply share survey observation for implants, seen in Figure 2.4. The private sector adjustment factor for female sterilization is consistent over time, reflecting the consistent trends seen in the contraceptive supply share estimates seen in Figure 2.4. The method with the highest estimated private sector adjustment factor is pills, the median estimate rising to approximately 3 in 2017.

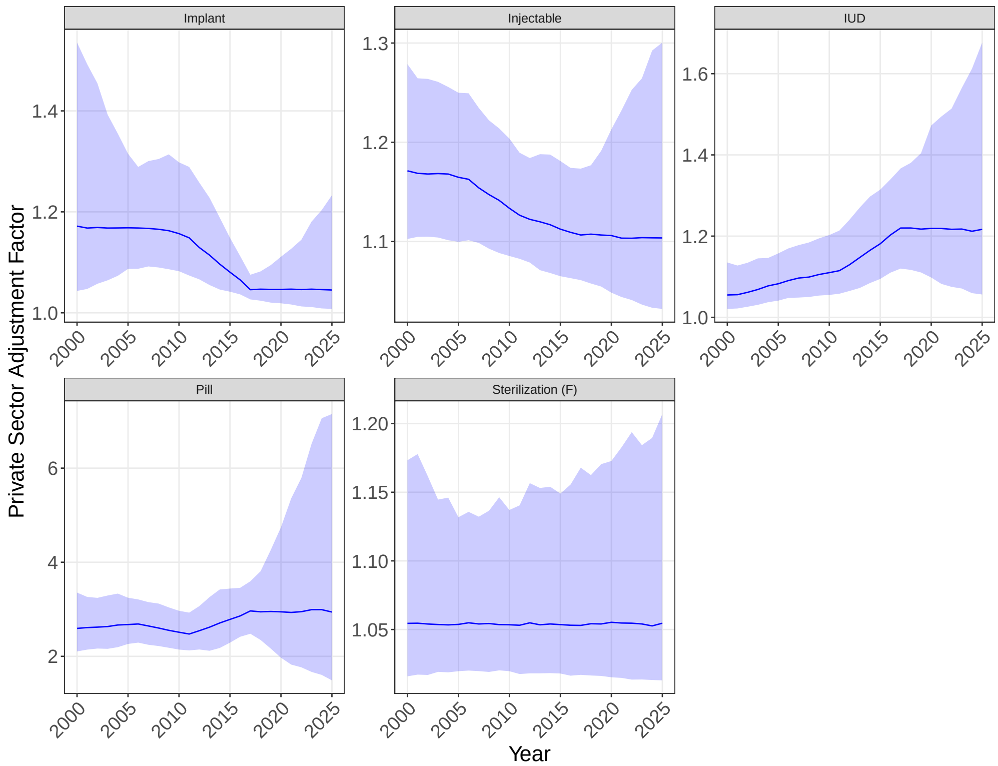


Figure 2.5: This plot illustrates the private sector adjustment factor over time for different contraceptive methods in Country 1. The solid lines indicate median estimates, while the shaded areas represent the 95% credible interval. Previously, private sector adjustment factors were fixed over time without any associated uncertainty. The enhanced calculation now produces a time-varying adjustment factor, reflecting both temporal changes in contraceptive supply share and associated uncertainty.

The private sector adjustment factor seen in Figure 2.5 was used to refine user counts for each contraceptive method, ensuring a comprehensive representation of the contraceptive market. Figure A.2 offers an overview of the user counts of each method captured in family planning visits in Country 1. The availability of samples of the private sector adjustment factor results in samples of adjusted user counts for each method. This allows us to summarise uncertainty in the resulting adjusted user counts. The figure illustrates numbers of users prior to private sector adjustment

($\theta_{c,s,t,m}$), along with median estimates and 95% credible intervals of the samples of adjusted user counts of each method ($\eta_{c,s,t,m,j}$). All contraceptive methods show an upward trend in the number of users from 2014 to 2022, indicating increased adoption of modern contraceptive methods over time. For example, the number of injectable users prior to adjustment in 2014 was 2661. In contrast, in 2022 the number of users was estimated to be 14203. The same trend in contraceptive use is seen for the adjusted number of users, with associated uncertainty. The width of the credible intervals generally increases over time, particularly after 2018. This reflects increased uncertainty in the estimates. This is reflective of the trends in uncertainty seen in the private sector adjustment estimates in Figure 2.5.

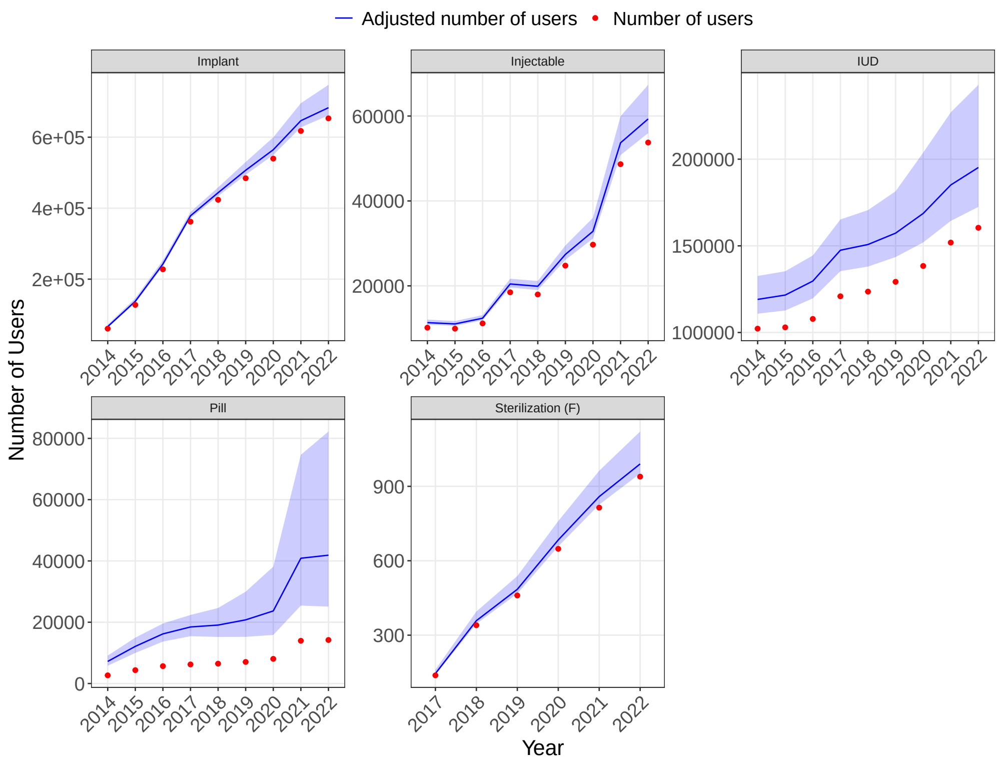
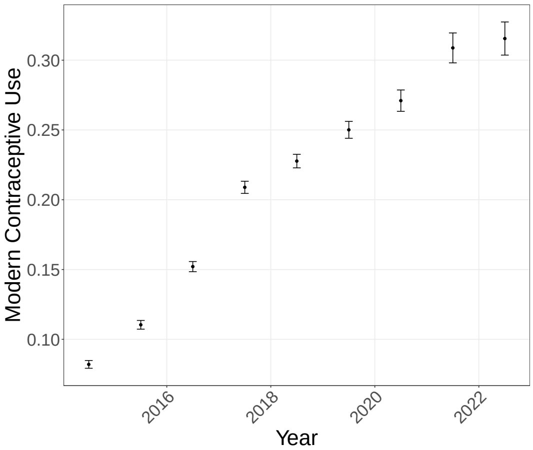


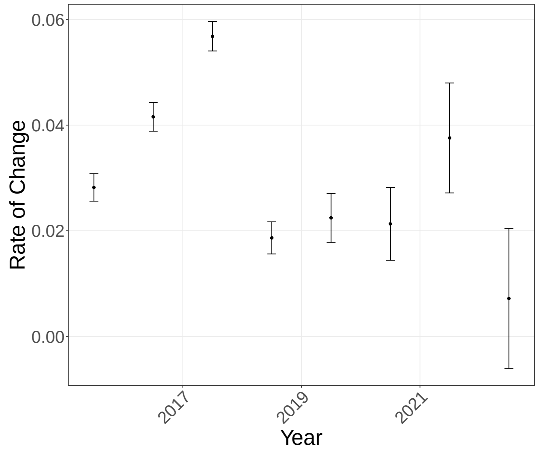
Figure 2.6: This plot illustrates the annual number of users by contraceptive method captured in family planning visits data in Country 1. The points reflect user counts before the private sector adjustment. The solid line represents the median estimate of adjusted users following the private sector adjustment, while the shaded area indicates the 95% credible interval associated with these estimates.

The estimates of adjusted user counts were then used to calculate EMU, as shown in Figure 2.7a. This plot illustrates EMU with uncertainty over time. The variability in the private sector adjustment factor influences EMU calculations, with point estimates summarised as medians and uncertainty represented by standard deviation. Estimates of mCPR show a steady increase in modern contraceptive use from 2014 to 2022. For instance, in 2014, EMU was 8.2%, rising to 31.5% in the latest estimate, marking a 20.5% increase over the period. The uncertainty associated with the adjusted user counts, as depicted in Figure A.2, is reflected in EMU results. Notably, the error bars in the plot illustrate increasing uncertainty in EMU over time. The standard deviation in 2014 is 0.3%, increasing to 1.2% in 2022. This allows us to temporally assess the uncertainty introduced during the private sector adjustment process in the output of the calculation.

When using EMU to inform model-based estimates of mCPR, we consider EMU rates of change, where the rate of change is defined as the annual difference between observations. In this work, we use EMU samples to obtain samples for these corresponding rates of change. This allows us to summarise EMU rates of change using point estimates and standard deviations, thereby incorporating the uncertainty of EMU into the EMU rates of change. Figure 2.7b illustrates rates of change in EMU over time with uncertainty. EMU rates of change range from 0.7% to 5.7%. The inclusion of standard deviations for EMU rates of change enhances our ability to more accurately capture the changes in modern contraceptive use. The increasing temporal uncertainty seen in EMU is directly reflected in the corresponding EMU rates of change, with the standard deviation increasing from 0.3% in 2015 to 1.4% in 2022.



(a) EMU over time.



(b) Annual rates of change in EMU over time.

Figure 2.7: These plots illustrate (a) EMU over time and (b) the corresponding annual rates of change in EMU over time for Country 1. Points represent estimates, and error bars represent standard deviations. EMU reflects the level of the contraceptive use captured by service statistics, while EMU rates of change measure how this contraceptive use is varying annually. Previously, EMU and the associated rates of change were treated as point estimates. The use of the enhanced EMU calculation allows for the quantification of uncertainty for both EMU and its rates of change.

2.4.2 Case Study: Country 2

We consider contraceptive commodities distributed to clients data in Country 2. Figure 2.8 illustrates the method mix captured by contraceptive commodities distributed to clients, showing the proportion of users for each method from 2012 to 2022. The data indicates that IUD were initially the most prevalent method, though usage has declined steadily from 46.4% in 2012 to 28.6% in 2022. Injectable use has decreased from 25.5% in 2012 to 9.9% in 2022. Other modern methods remained minimal throughout the period. The use of male condoms has fluctuated but remained relatively low, peaking in 2017 at 6.4% before decreasing again. Pill usage has also declined from 22.8% in 2012 to 7.5% in 2022. In contrast, implants have shown a substantial rise, starting from 4.8% in 2015 (the first year data was available) to becoming the most prevalent method at 49.4% in 2022. This shift suggests a growing preference amongst contraceptive users for long-term, reversible contraceptive methods such as implants over short-term or user-dependent methods like pills, injectables, and condoms.

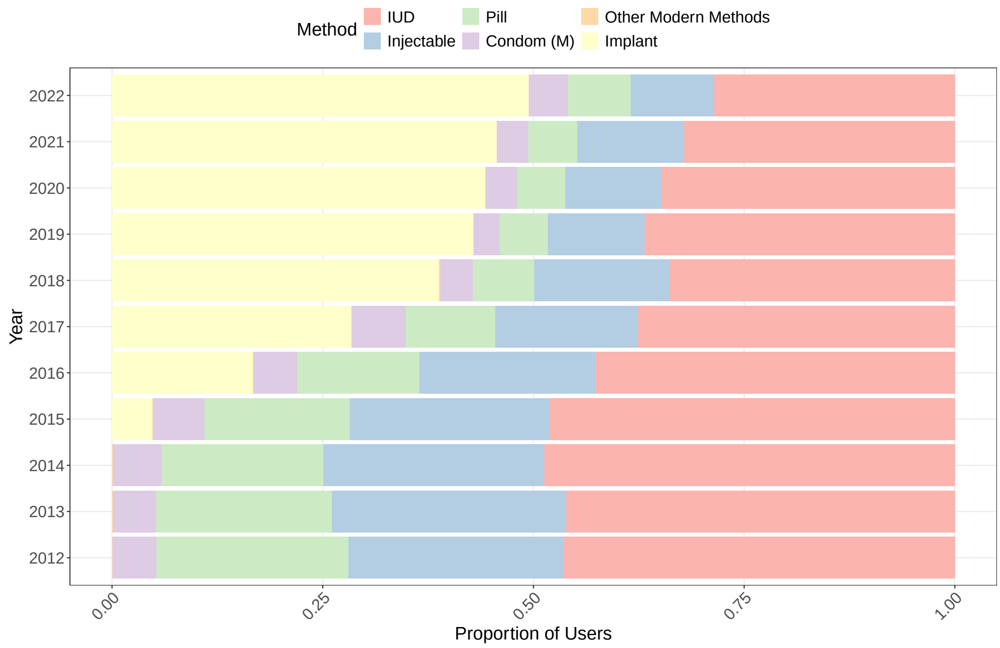


Figure 2.8: This stacked bar chart illustrates the proportion of users by contraceptive method captured in contraceptive commodities distributed to clients data in Country 2 from 2012 to 2022, prior to the private sector adjustment. The methods listed are described at the beginning of the chapter. The 'pill' refers to the oral contraceptive pill and 'sterilization (F/M)' is female/male sterilization respectively. Each bar represents a year, showing the distribution of users across different methods. The colours correspond to each contraceptive method, allowing for a visual comparison of trends in usage over the years.

Figure 2.9 illustrates the distribution of contraceptive supply by facilities over time for the methods documented in Country 2's data, namely implants, injectables, IUD, and oral contraceptive pills. The availability of survey observations varies across contraceptive methods in Country 2 since 2000. For implants and IUD, there is only one available DHS, conducted in 2018, while injectables and pills have additional DHS in 2005 and 2012. This variance in survey frequency impacts the credible intervals notably. This is particularly evident before 2018, with implants and IUD exhibiting generally higher uncertainty in estimates compared to injectables and pills. Since 2018, the year of the most recent survey for all contraceptive methods observed in Country 2, uncertainty has consistently increased over time for all contraceptive methods. Throughout the period, implants, injectables, and IUD are predominantly supplied by the public medical sector, while the private sector notably contributes to the supply of oral contraceptive pills. Estimates in trends in public medical sector contraceptive supply have are consistent for implants and IUD, due to the limited availability of DHS observations since 2000. For implants, injectables, and IUD, the data indicates that these methods are predominantly supplied by public medical and private hospital facilities, with no noticeable contribution from pharmacies or NGOs. Pharmacies appear to be the predominant source of supply within the private medical sector for contraceptive pills. However, the most recent DHS suggests a decrease in the pharmacy supply of contraceptive pills.

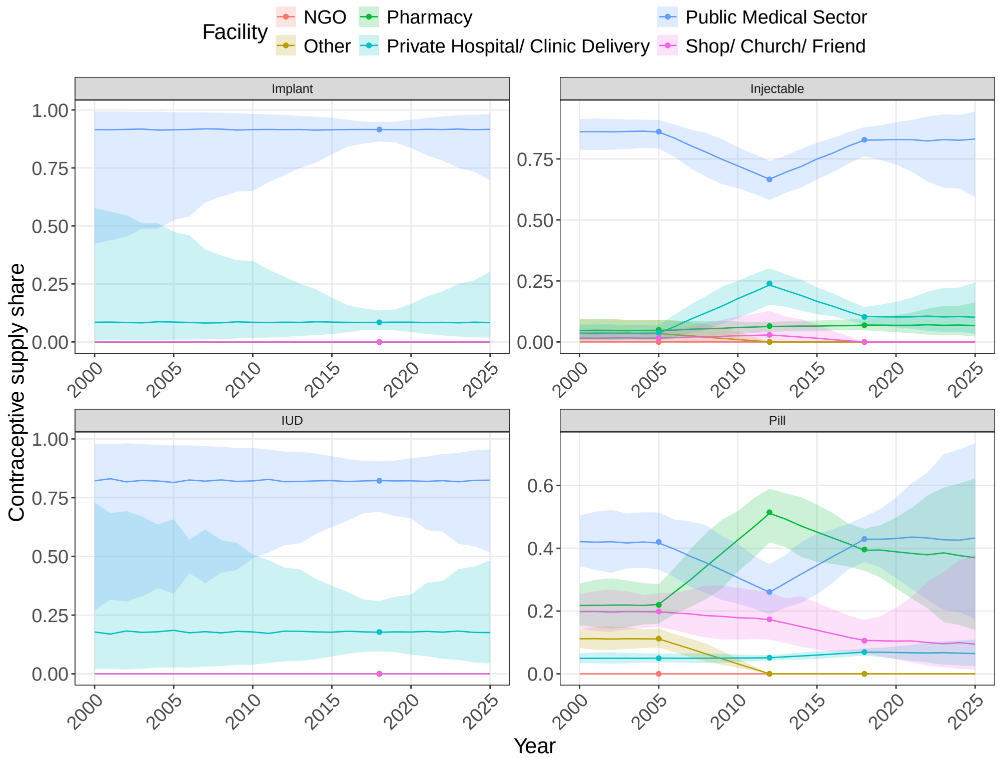


Figure 2.9: This plot illustrates estimates and projections of contraceptive supply share by facility type over time in Country 2, categorised by contraceptive method. The x-axis represents the years from 2000 to 2025, while the y-axis shows the contraceptive supply share ranging from 0 to 1. Different colors indicate various facility types. The solid line represents the median estimate, while the shaded areas depict the 95% credible interval. Points correspond to survey observations.

Data capturing the level of reporting into contraceptive commodities distributed to clients data for each facility in Country 2 is summarised in Table 2.2. Similarly to the Country 1 case study, the public medical sector is fully represented, whilst the private medical sector facilities vary from partially to not represented, and other is not represented in the data.

The subsequent private sector adjustment factor for each contraceptive method in Country 2 can be seen in Figure 2.10. As demonstrated by the plot, contraceptive supply share estimates directly influence the uncertainty associated with the resulting private sector adjustment factor estimates. This is particularly evident

Sector	**Facility**	**Reporting**
Public	Public Health Facilities and Community Health Services	Yes
Private	(Non-Governmental Organisations) NGO	Partially
Private	Private Hospital/Clinic Delivery	Partially
Private	Pharmacy	No
Other	Shop/Church/Friend	No
Other	Other	No

Table 2.2: This table summarises the reporting status of each facility type within different sectors: public, private, and other, in Country 2. The reporting levels are categorised as follows: "Yes" indicates that the facility type is fully represented in service statistics; "Partially" indicates partial representation; and "No" indicates absence from the data. This information is essential for adjusting for missing facilities during the private sector adjustment process and is a key component in calculating the private sector adjustment factor.

for implants and IUD. As illustrated in Figure 2.9, the DHS observation for these methods occurs in 2018, corresponding to the lowest uncertainty in the private sector adjustment factors. In contrast, in years where there is greater uncertainty in the contraceptive supply share, increased uncertainty can be seen in the private sector adjustment factor estimates. This is illustrated by the increased uncertainty in the 95% credible intervals seen in implants and IUD since 2018. In addition to this, the consistent trend in the median estimate of contraceptive supply share is reflected in the private sector adjustment factor for implants and IUD, the median estimate staying consistently at approximately 1.05, and 1.1, respectively over time. When considering the private sector adjustment factor for injectables and pills, the changing trends in contraceptive supply share are reflected in the estimates. Uncertainty is also reflected, as as time since the most recent DHS in 2018 increases, uncertainty increases. The estimated private sector adjustment factor for both pills and injectables has decreased since 2012.

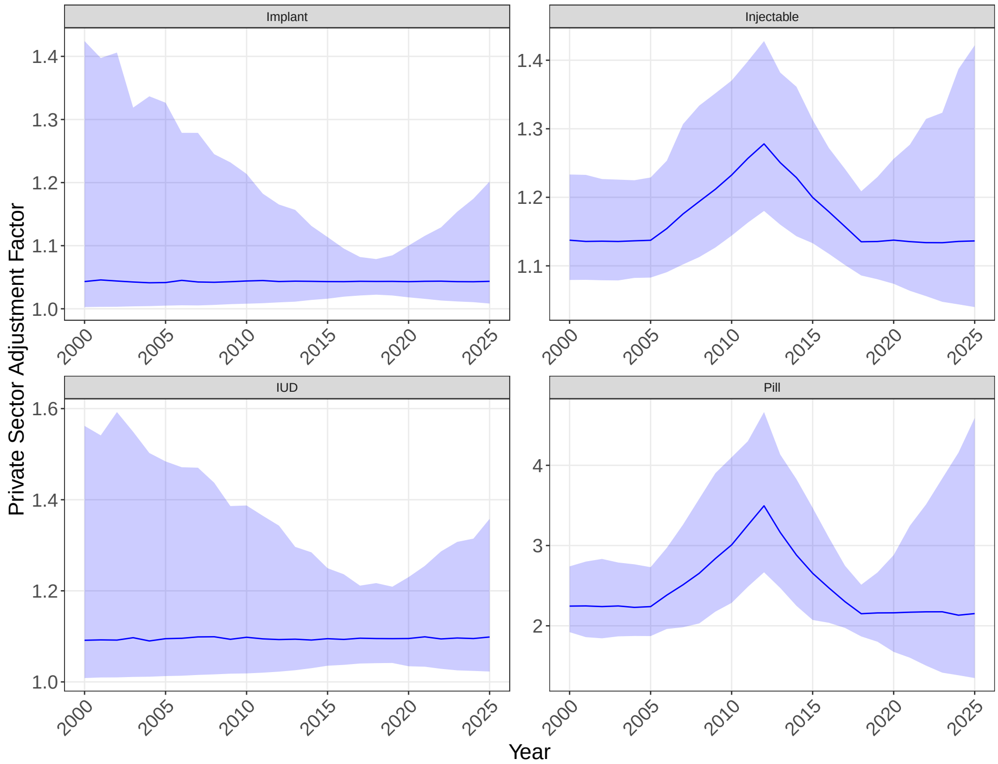


Figure 2.10: This plot illustrates the private sector adjustment factor over time for different contraceptive methods in Country 2. The solid lines indicate median estimates, while the shaded areas represent the 95% credible interval. Previously, private sector adjustment factors were fixed over time without any associated uncertainty. The enhanced calculation now produces a time-varying adjustment factor, reflecting both temporal changes in contraceptive supply share and associated uncertainty.

Figure 2.11 summarises unadjusted and adjusted user counts of each method captured in contraceptive commodities to clients in Country 2. In this case, there is data available from 2012 to 2022. Varying trends are seen across contraceptive methods over this time period. For example, the number of implant and IUD users have steadily risen since 2012, whilst pills and injectables have seen both decreased and increased uptake. The estimates obtained of adjusted user counts of pills show more extreme decrease than seen in the unadjusted counts from 2012 to 2019, accompanied by a decrease in uncertainty during this time. Similarly, in recent years, when accounting for missing private sector contributions, the adjusted counts show a sharper increase in pill use than observed in the unadjusted user counts. Appendix A includes additional plots that provide further comparison of adjusted user counts based on the previously established fixed private sector adjustment method.

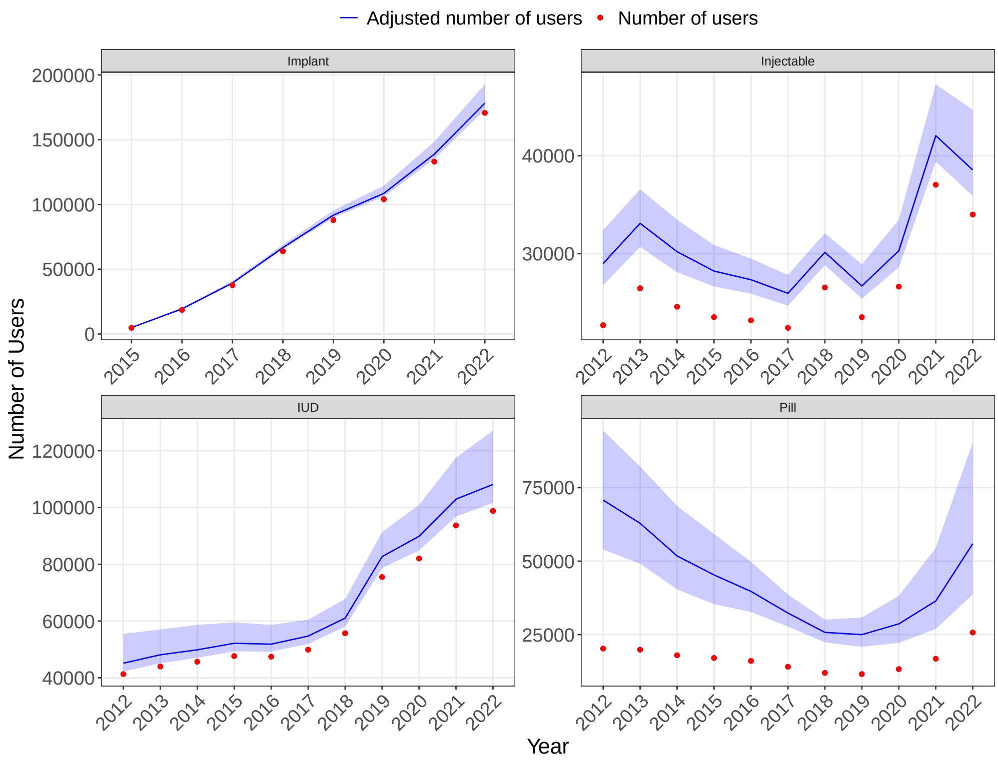
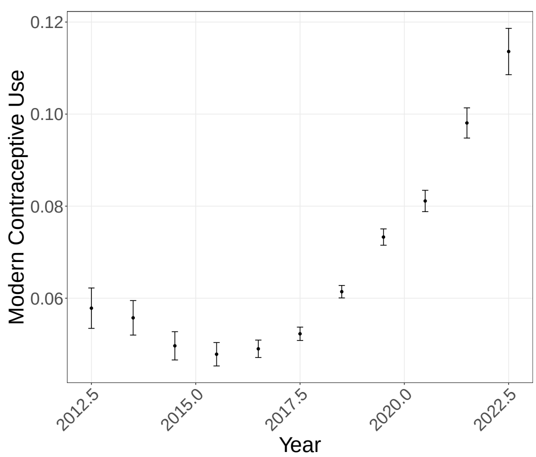


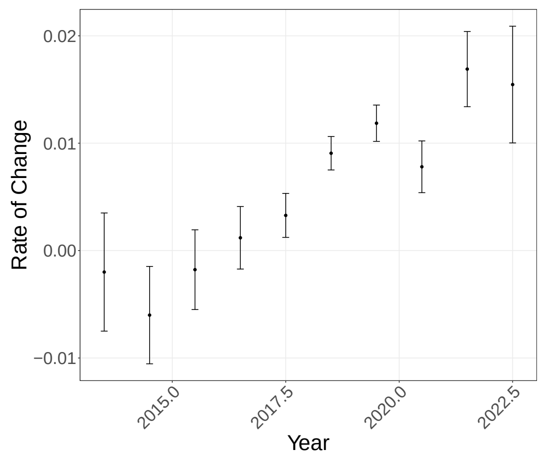
Figure 2.11: This plot illustrates the annual number of users by contraceptive method captured by contraceptive commodities distributed to clients data in Country 2. The points reflect user counts before the private sector adjustment. The solid line represents the median estimate of adjusted users following the private sector adjustment, while the shaded area indicates the 95% credible interval associated with these estimates.

EMU over time in Country 2 is depicted in Figure 2.12a. Levels in EMU are variable, decreasing from a point estimate of 5.8% to 4.8% from 2012 to 2015, and consistently increasing since, to the most recent estimate of 11.4% in 2022. Variation in uncertainty over time is illustrated by the change in error bars over time. The lowest uncertainty can be seen in 2018, with a standard deviation of 0.1%, corresponding to the period in which the lowest uncertainty can be seen in the private sector adjustment factors for all methods (Figure 2.10). In contrast, 2022 corresponds to the highest EMU uncertainty, with a standard deviation observation of 0.5%.

Figure 2.12b illustrates EMU rate of change over time in Country 2. The variation seen in EMU level in Figure 2.12a is evident in the rates of change observed here. The inclusion of uncertainty estimates, represented by error bars, highlights the importance of considering inherent variability rather than relying solely on point estimates. Higher standard deviations are observed in the years where there is higher uncertainty in EMU, specifically during 2013 to 2015 and 2021 to 2022. This shows that when accounting for EMU uncertainty, the rates of change in EMU are more volatile in these periods, particularly in recent years where growth in EMU is steeper but more uncertain.



(a) EMU over time.



(b) Annual rates of change in EMU over time.

Figure 2.12: These plots illustrate (a) EMU over time and (b) the corresponding annual rates of change in EMU over time for Country 2. Points represent estimates, and error bars represent standard deviations. EMU reflects the level of the contraceptive use captured by service statistics, while EMU rates of change measure how this contraceptive use is varying annually. Previously, EMU and the associated rates of change were treated as point estimates. The use of the enhanced EMU calculation allows for the quantification of uncertainty for both EMU and its rates of change.

2.5 Discussion

This chapter introduces an enhanced approach to calculating Estimates of Modern Use (EMU) from family planning service statistics, aiming to address some of the uncertainty inherent in the calculation process. Previously, the calculation of EMU relied solely on point estimates without considering the associated uncertainty in the inputs. The work here is motivated specifically by the need to quantify the uncertainty introduced when adjusting service statistics to reflect private sector contributions prior to calculating EMU.

The private sector adjustment applied to service statistics, accounts for missing private sector contributions in the data, and is crucial for ensuring that EMUs reflect the full contraceptive market. This work addresses three key aspects of the private sector adjustment calculation; potential variations in facilities reported to be partially reporting to the data, accounting for changes in contraceptive supply share across methods over time, and the uncertainty in estimates of contraceptive supply share, all of which can significantly impact the EMU. As a result, we now have a private sector adjustment factor for each method that varies over time, and has associated uncertainty, directly influenced by the time elapsed since the most recent DHS that the calculation relies on. This is in contrast to the previous approach, in which the private sector adjustment factor was fixed over time, and had no associated uncertainty.

To illustrate the effectiveness of the updated calculation process, the chapter presents two country-level case studies. We presented the impact of this updated approach on each step of the calculation process. Private sector adjustment factor estimates with uncertainty were propagated into the remaining steps of the EMU calculation process, adjusting the number of users of each contraceptive method and subsequently, calculating EMU. These case studies serve to demonstrate the direct influence of uncertainty in the input variables on the resulting uncertainty in EMU. In the case of Country 2, the varying uncertainty observed in contraceptive supply share directly accounts for the temporal changes in uncertainty with respect to private sector adjustment factor, and subsequently in EMU. In Country 1, the influence of increasing contraceptive supply share uncertainty was observed in EMU as increased standard deviation estimates in 2020 to 2022, when compared to the past.

Additionally, this work aims to enhance the use of EMU as a supplementary data source for informing estimates of modern contraceptive prevalence. This was achieved by extending our analysis to quantify uncertainty in EMU rates of change, a key aspect given EMU rates of change are used in FPET. Considering EMU rates of change in both case studies, as illustrated in Figures 2.7b and 2.12b, we observed that accounting for the variance in the EMU rate of change estimate gives insight into the inherent uncertainty in trends due to uncertainty in EMU. This demonstrates that by incorporating uncertainty, we can achieve a more accurate representation of contraceptive use trends, thus improving the reliability of EMU for informing estimates of mCPR. Furthermore, the inclusion of uncertainty in EMU rates of change could significantly influence how EMU is used in FPET, compared to relying solely on point estimates. With this in mind, future work could include an updated approach to the use of EMU in FPET.

In summary, this chapter contributes to advancing methods in annual monitoring of modern contraceptive use by providing a more sophisticated approach to calculating EMU. Overall, this results in a shift in how we interpret EMU, moving beyond solely relying on point estimates. By using this updated approach, decision makers can gain insights into the sensitivity of EMU to different sources of uncertainty, such as partial reporting, thereby enabling more informed decision-making. By quantifying uncertainty and considering potential sources of variation in the calculation process, it offers a more nuanced understanding of the implications of adjustments made on the resulting EMU, ultimately leading to more accurate results.

Data and software availability

Data availability

Contraceptive supply share data, including annual supply share estimates and model-based uncertainty estimates can be found at https://github.com/shaunamooney/shinyss2emu. Country-level service statistics data used in this analysis are confidential and cannot be made publicly available due to privacy concerns.

Software availability

All computations were performed in R (R Core Team [2021]). The code used to calculate EMU using the enhanced approach is available at the following GitHub repository: https://github.com/shaunamooney/shinyss2emu.

Competing interests

There are no competing interests to declare.

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CHAPTER 3

Enhancing the use of family planning service statistics using a Bayesian modelling approach to inform estimates of modern contraceptive use in low- and middle-income countries

Abstract

Background: Monitoring family planning indicators, such as modern contraceptive prevalence rate (mCPR), is essential for family planning programming. The Family Planning Estimation Tool (FPET) uses survey data to inform estimates and forecasts of family planning indicators, including mCPR, over time. However, reliance solely on surveys can lead to data gaps given that large-scale, population-health surveys are carried out on average every 3-5 years. Service statistics are a readily available data source that are routinely collected in conjunction with family planning service delivery. Various service statistics data types can be used to derive a family planning indicator called Estimated Modern Use (EMU). In a number of countries, annual rates of change in EMU have been found to be predictive of true rates of change in mCPR. However, it has been challenging to capture the varying levels of uncertainty associated with the EMU indicator across different countries and service statistics data types and to subsequently quantify this uncertainty when using EMU in FPET.

Methods: In this chapter, we present a new approach to using EMUs in FPET, to inform mCPR estimates. The new approach is based on using annual EMU rates of change as input, and accounts for uncertainty associated with the EMU derivation process. The approach also accounts for additional country-type-specific uncertainty. We assess the EMU type-specific uncertainty at the country level, via a Bayesian hierarchical modelling approach.

Results: We present model validation results and anonymised country-level case studies to highlight the impact of including EMU data with uncertainty in FPET when estimating mCPR. The validation results illustrate improved predictive performance with the inclusion of EMUs compared to using survey data only. Case studies provide additional insights into how including EMU data affects mCPR estimates in different country contexts. Together, the validation results and case studies demonstrate that EMUs can help countries more effectively monitor progress toward their family planning goals.

3.1 Introduction

Family planning supports the fundamental right of individuals to choose the number and timing of their children. Access to family planning greatly enhances health outcomes for women and children and helps reduce poverty (Cleland et al. [2006]). To effectively track progress toward country-level family planning goals, it is essential for countries to monitor current trends in family planning indicators, such as contraceptive prevalence and unmet need for contraception, and forecast future trends (Stover and Sonneveldt [2017]). This empowers countries to make data-driven, informed decisions towards achieving family planning goals.

The Family Planning Estimation Tool (FPET) is a Bayesian statistical model that is used to produce country-level estimates and forecasts of family planning indicators (Alkema et al. [2013], Cahill et al. [2018], Kantorová et al. [2020], Alkema et al. [2024c]). One of the key family planning indicators used to monitor progress is the modern contraceptive prevalence rate (mCPR), defined as the proportion of women reporting that themselves or their partner currently uses at least one modern contraceptive method.

While FPET traditionally relies on survey-based observations of family planning indicators, the intermittent nature of large-scale population-health surveys, conducted every 3-5 years on average, introduces data gaps. This intermittency poses a challenge to achieving data-driven model forecasts and estimates. To address this, we draw on routine health facility data, specifically family planning service statistics, which serve as a supplementary data source generated as a by-product of family planning service delivery.

Family planning service statistics are used to derive Estimated Modern Use (EMU), a family planning indicator that provides insight into modern contraceptive use (Track20 [2020, 2023]). Despite potential biases in EMU data, studies have demonstrated their utility in FPET to inform mCPR estimates in the absence of recent survey data (Magnani et al. [2018], Cahill et al. [2021]). To account for such biases, rates of change in EMU data, which are assumed to be unbiased with respect to rates of change in mCPR, can be used to inform mCPR estimates and forecasts where survey data are absent.

However, while annual rates of change in EMU estimates have been found to be predictive of true rates of change in mCPR, it has been challenging to capture and quantify the varying sources of uncertainty at the country level associated with this indicator. We present a new approach to using EMUs to inform mCPR estimates in FPET, accounting for both uncertainty associated with the EMU derivation process and the unexplained errors in country-specific EMU data series. Effectively quantifying this uncertainty ultimately improves the use of EMU data in FPET and results in improved accuracy and reliability of the EMU-informed estimates, enabling better tracking of mCPR trends.

There is growing interest in the use of non-standard data sources, such as service statistics, to provide frequent and up-to-date insights into population-level health indicators (Hung et al. [2020], Sawadogo-Lewis et al. [2021]). This is especially useful when informing decision making, particularly where 'gold standard' data such as household surveys are collected intermittently, not keeping up with the timelines of initiatives, therefore increasing the risk of relying on outdated data. To address this issue, researchers have explored the value of using various forms of non-standard data. For instance, researchers established a spatio-temporal model to combine survey data with routine health data to estimate malaria risk in Rwanda (Semakula et al. [2023]). Research into the coverage of maternal and child health services using routine health data further illustrates the use of readily available data to inform indicators (Maïga et al. [2021], Agiraembabazi et al. [2021]). Additionally, routine health data can offer insights into healthcare performance during crises (Turcotte-Tremblay et al. [2023]). These methods can allow for more responsive decision-making, reducing the risk of relying on outdated information. Beyond the use of routine health data, mobile phone data has been used to predict the spatial spread of cholera (Bengtsson et al. [2015]), and social media data has been used to track migration patterns (Alexander et al. [2022]). The work presented in this chapter, improving the use of family planning service statistics to refine estimates of a key family planning indicator such as mCPR, further advances progress in this field.

The remainder of this chapter is structured as follows: we begin with background, including an overview of FPET. This is followed by a section on service statistics. Next, we present our exploratory analysis and methodology. We then outline the model validation results, discuss the impact of EMU inclusion, and showcase country-level case studies to demonstrate the impact of EMU inclusion across various scenarios. We conclude with a final discussion.

3.2 Background

3.2.1 Estimating mCPR using the Family Planning Estimation Tool

FPET produces estimates and short-term forecasts of the modern contraceptive prevalence rate (mCPR) for women of reproductive age, by marital status (Alkema et al. [2013], Cahill et al. [2018], Kantorová et al. [2020], Alkema et al. [2024c]). mCPR is defined as the proportion of women who are users of modern methods of contraception, including female and male sterilisation, male and female condoms, hormonal methods, vaginal barrier methods, standard days method, lactational amenorrhea method, and emergency contraception. Interest lies in mCPR among married women of reproductive age (MWRA), unmarried women of reproductive age (UWRA), and all women of reproductive age (AWRA).

FPET primarily produces estimates that are informed by survey data. The statistical model is based on a Bayesian hierarchical B-spline transition model to capture long- and short-term changes in family planning indicators over time, comparable to an ARIMA(1,1,0) model with level-dependent drift (Alkema et al. [2024c]). The survey data model, that captures how survey data is assumed to relate to the true family planning indicators, accounts for various types of errors associated with the data (Alkema et al. [2024a]). Figure 3.1 illustrates FPET's survey-based estimates and forecasts of mCPR over time in a selected country (referred to as Country A) for AWRA, MWRA and UWRA. To ensure data confidentiality, we anonymise each country-level case study presented in this chapter.

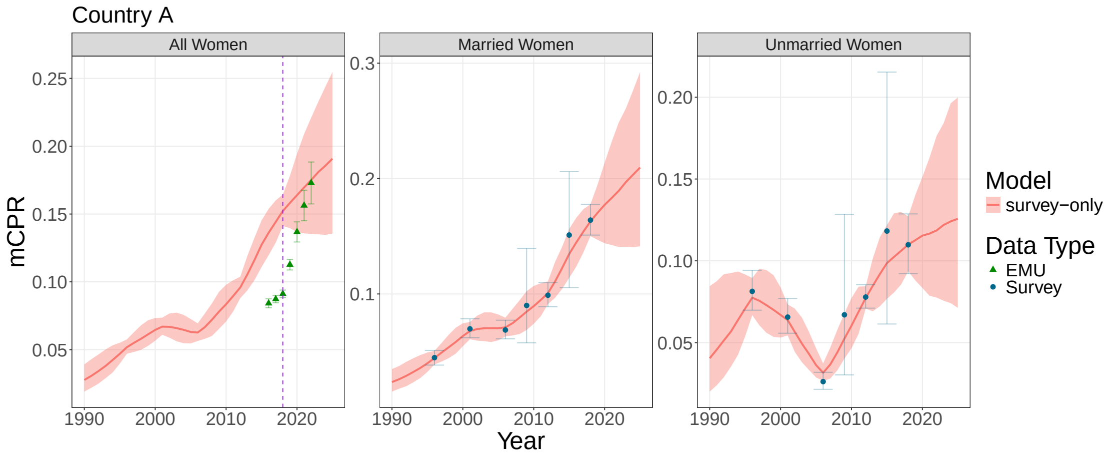

Figure 3.1: FPET estimates and forecasts of mCPR for AWRA, MWRA, and UWRA in Country A, using the survey-only model. The red solid line represents the median estimate of mCPR, with the shaded area indicating the 95% credible interval. Green points show EMU data, which were not used to fit the model but are included for reference. Blue points represent the survey data used in the model fitting. The error bars represent the 95% confidence interval associated with the data. The purple dashed line marks the year of the most recent survey.

3.2.2 Using service statistics data

Service statistics provide a readily available, supplementary data source to survey data that can be used to inform estimates of mCPR in the absence of recent surveys. This is illustrated for Country A in Figure 3.1. In Country A, the latest survey occurred in 2018 (indicated by the dashed vertical line). Service statistics data extend to 2022 and could offer more up-to-date insights. EMUs, derived from Country A's service statistics data for AWRA, are added to the same figure and suggest a faster rate of change since 2018, as compared to the survey-based forecasts. The open question is how to use such data appropriately, including considerations of inherent biases and uncertainties.

3.3 Service statistics

3.3.1 Health Management Information Systems

Service statistics are collected via health management information systems (HMIS), which have been implemented in many low- and middle-income countries to routinely collect and manage data on healthcare services delivered at facilities. The most common being the DHIS2 platform, an open-source HMIS used by many FP2030 pledging countries, that is, countries that pledged to take specific actions to expand access to voluntary, rights-based contraception (MEASURE Evaluation [2017], DHIS2, Family Planning 2030). We consider service statistics collected after the nationwide implementation of DHIS2.

3.3.2 Service Statistics and Estimated Modern Use

There are four types of family planning service statistics:

1. Number of contraceptive commodities, for example pill packets and intrauterine devices, distributed to clients (EMU-clients).

2. Number of contraceptive commodities distributed to facilities (EMU-facilities).

3. Number of times clients interacted with a provider for contraceptive services (FP visits).

4. Number of current contraceptive users of any method including those who are still using longer acting methods that were received in previous years (FP users).

The process of using service statistics to calculate EMUs was developed by Track20, a project dedicated to collaborating with and monitoring progress of countries involved in the FP2030 initiative (Track20 [2023]). Further details of this calculation can be found in Mooney et al. [2024a]. EMUs are classified into one of the four data types, based on the service statistics used in their calculation. All data in this analysis were sourced from service statistics collected in 2023. The EMU dataset includes 344 observations from 23 countries. The volume and types of data vary by country; for instance, some countries have data from multiple EMU data types, while others have data from only one.

3.4 Exploratory Analysis

Figure 3.1 introduced survey-based model estimates of the level of mCPR in Country A, along with EMUs. When including EMUs in FPET, we consider EMU annual rates of change. Using survey-based model estimates of the level of mCPR, we can also derive survey-based annual rates of change in mCPR. This enables us to compare the rates of change observed in EMUs with those based on survey-only mCPR estimates. Figure 3.2 presents examples of EMU rates of change and survey-based mCPR rates of change for six countries and three EMU data types. Error bars provide insight into the uncertainty associated with each EMU rate of change observation, derived during the calculation process (Mooney et al. [2024a]).

Observation-level uncertainty varies significantly across countries, as shown in Figure 3.2. For instance, EMUs in Country C and Country D tend to have higher uncertainty compared to the other countries shown. Uncertainty also fluctuates within each country, for example, in Country A, Country B, and Country C, the plot illustrates increasing EMU uncertainty over time. Generally, when taking into account observation-specific uncertainty, we can see that EMU can capture survey-informed mCPR rates of change, but there are notable deviations to be considered within countries and across types.

Figure 3.2 provides insight into how well EMU can capture survey-informed mCPR rates of change in each country. Given that this is better evaluated during survey-informed years, we focus on observations prior to the most recent survey year, represented using the purple dashed line. In Country A, survey-based rates of change in 2017 and 2018 are at the upper bounds of the 95% confidence interval associated with EMU-based rates of change. Countries B and C both have only one observation prior to the survey year. While Country C's observation captures the survey-informed estimate, Country B's does not. In Country D, the absence of EMUs prior to the most recent survey makes it difficult to evaluate how well EMUs track mCPR trends. EMUs in Country E capture trends in survey-informed mCPR reasonably well. Initially in Country F, there is considerable variation in the EMU trends, however, more recent EMU observations show improvement in capturing survey-informed mCPR rates of change.

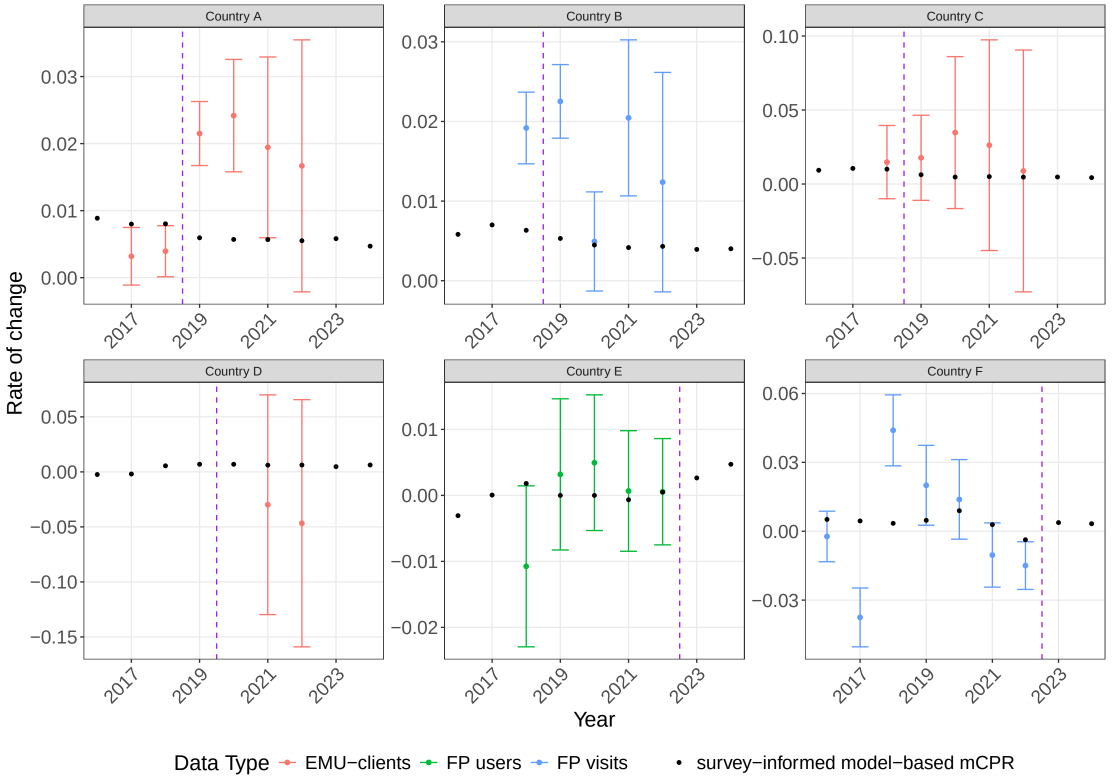

Figure 3.2: Rates of change in EMU and survey-informed model estimates of mCPR over time for Country A, Country B, Country C, Country D, Country E and Country F. Point colors represent EMU data type for each country. The error bars represent the 95% confidence interval associated with the data. The purple dashed line marks the year of the most recent survey.

Figure 3.3 provides an overview of rates of change in EMU (ΔEMU) versus rates of change in survey-informed mCPR (ΔP), for all data observed prior to the most recent survey in all countries in the database. The plot reveals that EMU-facilities and FP users display greater variation than EMU-clients and FP visits. In general, the changes in EMU data are dispersed around the identity line. However, differences across countries are notable. For example, in the FP users plot, the country represented in green shows some of the most extreme variations. Similarly, in the EMU-facilities plot, the country represented in pink displays more variability than the country represented by the orange data points. By ensuring our model incorporates cross-country variation in addition to type-specific variation, we can better capture these relationships. This further motivates our goal for an EMU data model in FPET that captures country-specific contexts, specifically, how well EMUs can predict trends in mCPR, while also accounting for observation-specific uncertainty.

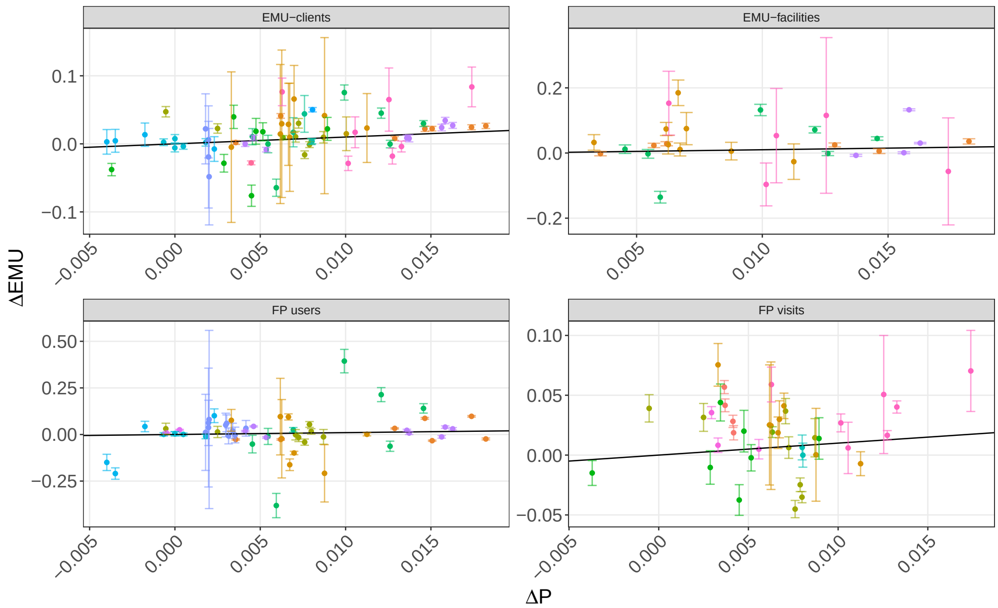

Figure 3.3: Scatterplot of changes in EMU (ΔEMU) versus changes in survey-informed model mCPR estimate (ΔP) by EMU data type, coloured by country. The error bars represent the 95% confidence interval associated with the data. Black lines represent the identity line ($\Delta EMU = \Delta P$).

3.5 Methodology

We introduce an EMU data model for use in FPET to inform estimates and forecasts of mCPR. This model incorporates recent advancements in EMU uncertainty quantification, using observation-specific uncertainties derived during the EMU calculation process. In addition, we capture additional country, type specific uncertainties informed by a set of hierarchically estimated variance hyperparameters. The Bayesian Hierarchical model used to estimate these hyperparameters is outlined in the next section.

3.5.1 EMU data model

For the EMU data model within FPET, we define $\Delta z_{c,d,t}$ as the annual rate of change in EMU for country c, data type d, and year t, and $s_{c,d,t}$ as the corresponding standard deviation. Then for $\Delta z_{c,d,t}$ the model is specified as follows:

$$\Delta z_{c,d,t}|\Delta\rho_{c,t}, s_{c,d,t}, \sigma_{c,d} \sim \mathrm{N}(\Delta\rho_{c,t}, s^2_{c,d,t} + \sigma^2_{c,d}), \tag{3.1}$$

where $\Delta\rho_{c,t}$ represents the annual rate of change in mCPR for country c, at time t, observation-specific uncertainty is a data input, and $\sigma^2_{c,d}$ is an unknown variance parameter for country c and data type d. This model assumes that trends in EMUs directly correspond to trends in true mCPR, with deviations away from this relationship attributed to observation-specific uncertainty and country- and type-specific uncertainty.

The hierarchical model for the country-type variance is as follows:

$$\log(\sigma_{c,d})|\theta_d, \tau \sim \mathrm{N}(\theta_d, \tau^2), \tag{3.2}$$

where the log formulation for $\sigma_{c,d}$ ensures the necessary positivity constraint, θ_d refers to the type-specific mean and τ to the standard deviation of log-transformed standard deviation parameters. The hierarchical model results in estimates for $\sigma_{c,d}$ that are based on data from the specific country-type setting where available, with shrinkage towards type-specific means in data-limited settings.

3.5.2 Estimating hyperparameters

To estimate the hyperparameters θ_d and τ used in the EMU data model, we fit the Bayesian hierarchical model to training data from multiple countries and data types, that leverages information sharing across countries and data-types. Specifically, we use training data comprising of all EMU data and mCPR estimates available prior to the most recent survey, denoted as $\Delta z^*_{c,d,t}$ and $\Delta\rho^*_{c,t}$. This training dataset includes 203 observations of EMU and mCPR estimates across 19 countries.

The hierarchical model allows the estimates of θ_d and τ to be informed by data from all countries in the training dataset. This means that even if there is limited data from a particular country, the estimates benefit from information being pooled across all countries in the dataset. The observed differences between rates of change in EMU and rates of change in mCPR in the training dataset, along with observation-specific uncertainties, directly inform our estimate of data-type specific log standard deviation (θ_d) and cross-country variance (τ) as follows:

$$\Delta z^*_{c,d,t} - \Delta \rho^*_{c,t} | \sigma_{c,d} \sim \mathrm{N}(0, s^2_{c,d,t} + \sigma^2_{c,d}), \tag{3.3}$$

where, as before,

$$\log(\sigma_{c,d}) | \theta_d, \tau \sim \mathrm{N}(\theta_d, \tau^2). \tag{3.4}$$

Priors for θ_d and τ are specified as a Normal distribution and a half-Cauchy distribution, respectively (Gelman [2006], Polson and Scott [2012]).

$$\theta_d \sim \mathrm{N}(0, 2^2), \tag{3.5}$$

$$\tau \sim \mathrm{C}^+(0, 1). \tag{3.6}$$

3.5.3 Inclusion of EMU data in FPET

FPET is used to produce estimates for a particular country, using data from that country alone (New et al. [2017], Alkema et al. [2024b]). The EMU data model used in FPET is the one presented above, using point estimates of the hyperparameters:

$$\log(\sigma_{c,d}) | \hat{\theta}_d, \hat{\tau} \sim \mathrm{N}(\hat{\theta}_d, \hat{\tau}^2), \tag{3.7}$$

where $\hat{\theta}_d$ is the estimated overall type-specific uncertainty and $\hat{\tau}^2$ is the estimated across country variance, estimated from the training data.

3.6 Results

3.6.1 Estimates of the Bayesian hierarchical model hyperparameters

Estimates of θ_d are summarised in Table 3.1. The smallest standard deviation (SD) estimate, $\hat{\theta}_d$, is associated with EMU-clients data, at -4.06 (95% credible interval (CI): (0.01, 0.03) on the original scale), while the largest SD estimate is associated with the EMU-facilities data type, at -2.77, on the log scale (95% CI: (0.03, 0.10)). SD estimates for FP visits and FP users are -3.56 (95% CI: (0.01, 0.06)) and -3.10 (95% CI: (0.02, 0.08)), respectively. The estimate of $\hat{\tau}$, which captures cross-country variation, is 0.84.

Table 3.1: Summary of data-type specific standard deviation estimates, ($\hat{\theta}_d$), posterior standard deviations (SD($\hat{\theta}_d$)) on the log scale, and the 95% credible intervals (CI) for $\hat{\theta}_d$ back-transformed to the original scale.

Data type	N	$\hat{\theta}_d$	SD($\hat{\theta}_d$)	95% CI for exp($\hat{\theta}_d$)
EMU-clients (d = 1)	73	-4.06	0.27	(0.01, 0.03)
EMU-facilities (d = 2)	30	-2.77	0.41	(0.03, 0.10)
FP visits (d = 3)	60	-3.56	0.35	(0.01, 0.06)
FP users (d = 4)	40	-3.10	0.31	(0.02, 0.08)

3.6.2 Global findings: Validation results

To evaluate model performance, we use an out-of-sample, leave-one-out validation exercise. In this context, this process involves excluding the most recent survey observation for each country during model fitting and using these excluded observations as test points. This validation method is intended to replicate a typical use case of the model. Performance was measured using several metrics including coverage and prediction errors. We evaluated both MWRA and UWRA model results for what we will term the survey-only model and the survey+EMU Model.

In cases where multiple types of service statistics are available, there is a data type deemed most appropriate for use in FPET during the data review process (Mooney et al. [2024a]). When evaluating the impact of the updated EMU model framework on performance and estimates, we focus specifically on results using the selected data type for each country.

Table 3.2 presents model validation results of mCPR obtained using the survey-only model and the survey+EMU model, for MWRA and UWRA . This provides an overview of the validation results, highlighting coverage, mean error (ME), mean absolute error (MAE), and root mean square error (RMSE). The ME indicates the average bias in model predictions, with positive values reflecting under-prediction.

The MAE measures the average magnitude of the errors in the model's predictions, indicating how far the predictions are from the test observation, regardless of direction. The RMSE gives insight into the variation of the error terms.

Across all metrics the survey+EMU model consistently outperforms the survey-only model. For MWRA, incorporating the EMU data model reduces the ME from 0.3 to 0.1, indicating a reduction in bias when including EMU. Since ME indicates the overall bias of predictions, that is, whether the model systematically overestimates or underestimates, a ME closer to zero suggests that the model's predictions are more balanced, with less systematic bias. Improvement in model performance is further supported by a reduction in MAE from 2.9 to 2.8, indicating errors of smaller magnitude. Additionally, the RMSE decreases from 3.7 to 3.5, indicating a reduction in the variability of the errors. Coverage remains at 95.7% for both models.

Predictability for UWRA estimates also improve with the inclusion of the EMU data, as reflected by the reduction in ME from 0.2 to -0.01, which points to reduced bias. The RMSE for UWRA decreases slightly from 2.9 to 2.8, highlighting a modest improvement in prediction accuracy. Coverage increases from 90.9% to 95.5%, indicating an improvement in the models ability to accurately project the test survey observation within the uncertainty bounds.

Table 3.2: Summary of validation results for survey-only and survey+EMU models, for MWRA and UWRA mCPR estimates, highlighting coverage, mean error (ME), mean absolute (MAE) and root mean square error (RMSE).

Marital Status	Model	N	Coverage	ME	MAE	RMSE
Married	Survey-only	23	95.7%	0.3	2.9	3.7
Married	Survey+EMU	23	95.7%	0.1	2.8	3.5
Unmarried	Survey-only	22	90.9%	0.2	2.3	2.9
Unmarried	Survey+EMU	22	95.5%	-0.01	2.3	2.8

3.6.3 Global findings: Impact of inclusion of EMU in FPET

We evaluated the impact that incorporating the EMU data model into FPET has on mCPR estimates and forecasts. We compared mCPR estimates for 2023 obtained using the survey-only model to those derived from integrating both the survey and EMU data models. It is important to note that, particularly due to country-level variability, the overall uncertainty associated with EMUs can be substantial. As such, we expect that in some settings, the inclusion of EMUs may have minimal impact, which demonstrates one of the model's strengths. We illustrate country-level case studies in the next section that highlight this.

Figure 3.4 illustrates the differences in mCPR point estimates, by percentage points, across all countries in the database, categorized by marital status and EMU data type. A positive difference in mCPR indicates an increase when the EMU data is included compared to when only surveys are used. The use of EMU-clients EMUs results in the largest impact overall, observing a maximum increase in mCPR of 3.5 percentage points (pp), 4.2pp and 1.3pp, for AWRA, MWRA and UWRA estimates respectively. FP users largest impact on point estimates of mCPR was 1.2pp, 1.5pp and 0.8pp on AWRA, MWRA and UWRA respectively. In terms of the use of FP visits, the largest change in point estimates was 1.5pp, 1.6pp, and 1.7pp; having the most impact on UWRA mCPR estimates in 2023. All data types show a positive median difference in mCPR estimates for UWRA, suggesting that supplementing the survey model with the EMU data model generally increases mCPR estimates for UWRA. EMU-clients data has the most variation in terms of point estimate differences, ranging from a decrease of 3.7pp to an increase of 4.2pp when considering MWRA estimates for example. The median point estimate difference when considering the use of FP visits is 1.2pp, 1.3pp and 0.8pp for AWRA, MWRA and UWRA, with the plot highlighting that these are the highest median point estimate differences across all data types. In terms of uncertainty with respect to model estimates, measured by the width of credible intervals, the inclusion of EMUs has no substantial effect.

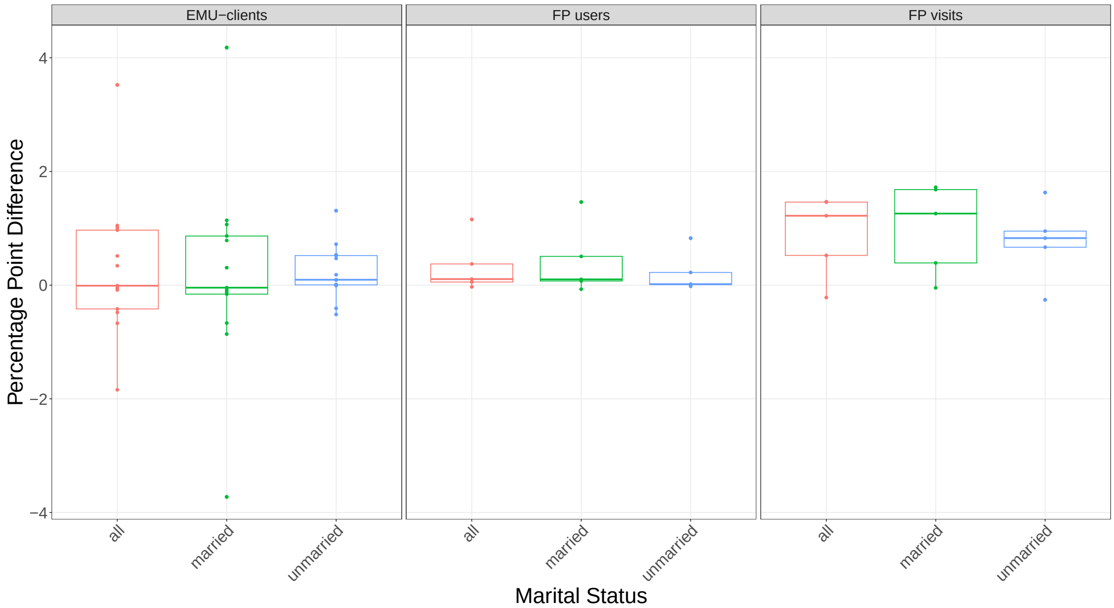

Figure 3.4: Boxplot of point estimate differences by marital status and data type, where the difference is defined as the mCPR estimate obtained with EMUs minus the mCPR estimate without EMUs (survey-only).

3.6.4 Country-level case studies

To illustrate the impact of including the EMU data model at the country-level, we provide case studies from six countries in the EMU 2023 database. Figure 3.5 highlights model results obtained using the survey-only and survey+EMU models for the six case study countries previously introduced in Figure 3.2. Results for all remaining countries can be found in Appendix B.

When evaluating the impact that the inclusion of EMUs have on mCPR estimates at the country-level, there are three key components to consider. One key factor is observation-level uncertainty: when uncertainty is high, the impact on model results tends to be smaller. Another important consideration is how well EMUs align with or reflect survey-based mCPR estimates in a given country. Figures 3.2 and 3.3 highlight the differences in both observation-level uncertainty, and how well EMUs align with mCPR across countries. Finally, the interval since the last survey is crucial: if a recent survey is available, the inclusion of EMUs will have little effect, while a longer interval can result in EMU inclusion having larger effect on estimates.

Country A provides an example of a context where observation-level uncertainty associated with EMUs is low, as illustrated by narrow error bars, and EMUs show improvement in tracking mCPR during survey-informed years. As a result, the inclusion of EMUs have substantial impact on mCPR estimates when compared to the survey-only estimates. Recent EMU trends appear to be increasing more rapidly than the model-based mCPR estimates, potentially indicating a recent uptake in modern contraceptive use that has not been captured by a survey yet. When examining the 2023 model results, we observe increases of 3.5pp, 4.2pp and 0.7pp for AWRA, MWRA and UWRA compared to using the survey only model.

Country B provide examples of contexts where observation-level uncertainty associated with EMUs is low, as illustrated by narrow error bars, however we don't have any EMU data before during survey-informed years to indicate EMUs are tracking mCPR well. In Country B, recent EMU trends appear to be increasing quicker than the model-based mCPR estimates, suggesting a recent increase in modern contraceptive use that has yet to be reflected in survey data. Point estimates of mCPR increase by 1.5pp, 1.7pp and 1pp for AWRA, MWRA and UWRA when including EMUs compared to the survey-only model.

Country C presents a context with limited data prior to the most recent survey. However, the single available observation indicates that EMUs were tracking mCPR trends well during the limited, survey-informed period. Observation-level uncertainty associated with EMUs is increasing, as shown by widening the error bars, which reduces the impact of more recent EMU values. That said, including EMU results leads to a larger estimated increase in mCPR in the years since the most recent survey, compared to using surveys alone. Specifically, increases of 1pp for AWRA, 1.1pp for MWRA, and 0.7pp for UWRA are observed compared to the survey-only model.

In Country D, there is no EMU data available prior to the most recent survey. EMU data are collected for MWRA, and as such, these data are used to inform MWRA mCPR estimates in FPET. Unlike the previous case studies, EMU data show a decline in contraceptive use in the years since the most recent survey. This impacts model estimates in 2023 with a 0.8pp decrease in mCPR when including EMU data when compared to the survey-only model results.

We use Country E and Country F as illustrative examples to demonstrate the impact of using EMU data in contexts where there has been a recent survey (both countries conducted surveys in 2022). As expected, the inclusion of EMUs has minimal effect on mCPR estimates in these case studies.

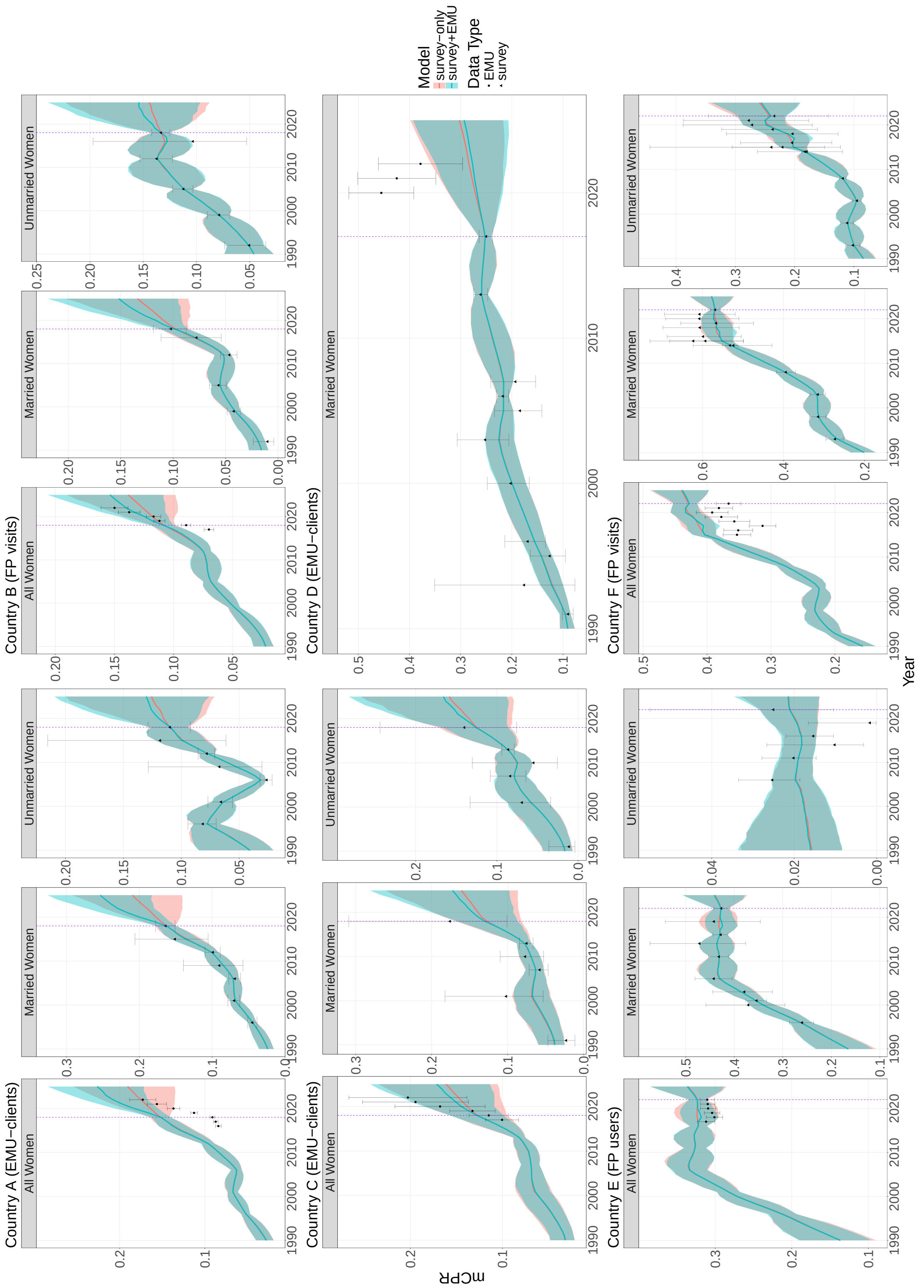

Figure 3.5: Estimates of mCPR for MWRA, UWRA, and WRA in Country A, Country B, Country C, Country D, Country E, and Country F. Solid lines indicate median estimates of mCPR, shaded regions show the 95% credible intervals. Results in red highlight the use of the survey-only model. Results in blue highlight the use of surveys and EMU. The error bars represent the 95% confidence interval associated with the data. The purple dashed line marks the year of the most recent survey.

3.7 Discussion

This chapter introduces an EMU data model framework designed to directly inform mCPR estimates and forecasts within FPET in the absence of recent survey data. Our approach uses the latest advancements in the EMU calculation process, allowing us to incorporate a decomposition of EMU uncertainty into FPET for the first time. The decomposition includes uncertainties at the observational level as well as country, type-specific uncertainties.

By taking into account observation-specific uncertainty in the EMU data model, observations with larger errors have less impact when used to inform mCPR estimates and forecasts at the country level. Previously, this type of uncertainty was not captured as EMUs were presented as point estimates. The results for six case study countries, highlight the uncertainty variation both across countries and over time within each country. This underscores the importance of incorporating observation-specific uncertainties when modelling EMU in FPET, as it allows for a more accurate representation of EMU rates of change.

In addition, the uncertainty decomposition provides flexibility in handling overall country-type specific uncertainty variations across countries. Previously, the EMU data model uncertainty was assessed solely by data type, which could lead to overdispersion in some countries and under-dispersion in others (Cahill et al. [2021]). The updated approach is more nuanced and can reduce uncertainty in countries where EMU data have effectively tracked mCPR in the past.

Using survey and EMU data available in 2023, we performed out-of-sample validation to assess model predictive performance, comparing performance to the survey-only model as a baseline. It was established that the inclusion of EMU in this manner in addition to the survey model in FPET improved model predictive performance. We saw an improvement across all validation error metrics when predicting both MWRA and UWRA survey observations of mCPR. Additionally, an increase in coverage for UWRA highlights the benefit of using EMU to inform the population for which service statistics have been collected, given in most cases this is for all women. Previously, EMU were solely used to inform estimates for MWRA and subsequently would have had no impact on UWRA estimates when used (Cahill et al. [2021]).

When evaluating the impact of EMU inclusion on 2023 mCPR estimates, we observed maximum impacts of 3.5 percentage points for all women of reproductive age, 4.2 percentage points for married women of reproductive age, and 1.6 percentage points for unmarried women of reproductive age with the use of EMU data. Due to country-level variability, the uncertainty associated with EMUs can be substantial, and in some settings, their inclusion has minimal impact, highlighting one of the model's strengths.

Six country-level case studies were presented in the chapter to showcase variation in EMUs across countries, and subsequently, the impact that EMU inclusion has on mCPR estimates and forecasts. There were examples to illustrate the minimal impact EMU will have on model results when there is a recent survey available. Conversely, there were also examples showcasing the use of EMU in situations where there is a survey-absent time period of at least five years. In this case, the use of EMU could have significant impact on mCPR estimates, with impact varying by country and data type. Moreover, each case study provided insight into the impact at a country-level of different levels of observation-specific uncertainty. In some cases, more recent EMUs are associated with higher uncertainty, which reduces their impact on model estimates. In other cases, observation-specific uncertainty is generally low, leading to a greater influence on mCPR estimates.

The work presented in this chapter contributes to empowering countries to track and highlight progress toward their family planning goals in a timely and accurate manner. Updates to the EMU data model and FPET mark a significant advancement in family planning modelling. By extending the EMU data model, we can ultimately help to better inform estimates and forecasts of mCPR for married and unmarried women of reproductive age, aiding countries to more comprehensively monitor progress towards their family planning goals. By providing more accurate and inclusive mCPR estimates, these improvements strengthen the ability of countries to track and achieve their family planning objectives.

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Conflicts of interest

There are no conflicts of interests to declare.

CHAPTER 4

`ss2emu`: An R Package for Calculating Estimated Modern Contraceptive Use using Family Planning Service Statistics

Abstract

Family planning service statistics can be used for monitoring contraceptive use, with Estimated Modern Use (EMU), derived from family planning service statistics, serving as a readily available indicator for evaluating family planning programs. Recent updates to the EMU derivation process have incorporated uncertainty at the observation level, but existing tools were limited in their computational capabilities to accommodate these changes. To address this, we developed `ss2emu`, an open-source R package designed to perform the necessary calculations for EMU derivation directly in R. In addition to the R package, we developed a Shiny App that provides a user-friendly interface, enabling Monitoring and Evaluation (M&E) officers to upload data, review results through visualisations, and export updated outputs. Together, these tools generate informative visualisations and produce a reproducible database for use in the Family Planning Estimation Tool (FPET),

a web application that is a country-specific implementation of the estimation approach for contraceptive prevalence and unmet need for family planning used by the United Nations Population Division (UNPD). This scalable and user-friendly solution for EMU derivation integrates with existing workflows, empowering users to make more informed decisions while evaluating family planning progress.

4.1 Introduction

There is growing interest in the use of routinely collected data to inform population-level indicators. In this paper, we discuss the use of family planning service statistics to inform estimates of the modern contraceptive prevalence rate (mCPR), defined as the proportion of women using modern contraception methods, in low- and middle-income countries (LMICs). These service statistics, which are routinely collected as part of facility-based family planning service delivery, provide a valuable data source for understanding annual trends in contraceptive use. The Family Planning Estimation Tool (FPET) uses both national survey data and service statistics as inputs to produce estimates and short-term forecasts of family planning indicators, such as mCPR, in LMICs (Alkema et al. [2013], New et al. [2017], Cahill et al. [2018], Kantorová et al. [2020], Alkema et al. [2024c]).

To use service statistics to inform mCPR with FPET, they must first be transformed from a count based metric into Estimated Modern Use (EMU), which represents a biased estimate of the proportion of modern contraceptive method users (Track20 [2020]). This transformation process, known as the SS-to-EMU calculation, has traditionally been performed using the Excel-based SS-to-EMU Tool (Track20 [2023]). Monitoring and Evaluation (M&E) officers, who are family planning data experts trained under the Track20 project, use this tool to collate and review service statistics and derive EMUs for their countries. However, recent advancements in the EMU calculation process, specifically the introduction of steps to quantify uncertainty at the observation level, have introduced complexities that exceed the computational capabilities of the current tool (Mooney et al. [2024a,b]).

We developed `ss2emu`, an open-source R package designed to perform the SS-to-EMU calculation within R (R Core Team [2021]), in a scalable and user-friendly way. The `ss2emu` R package extracts service statistics from a completed SS-to-EMU excel-based tool and performs the necessary calculations to derive EMU using the advanced calculation process. Given the widespread use of, and familiarity with the excel-based SS-to-EMU Tool, it was important to develop a solution that would integrate with existing workflows. This integration provides a robust and reliable way to obtain EMUs with uncertainty while complementing the existing practices of M&E officers.

Furthermore, we developed a Shiny web application (App), used in conjunction with the R package, adding a user-friendly interface, allowing M&E officers to upload their files, review results through visualisations, and export updated outputs (Chang et al. [2024]). These outputs include a database that can be directly used in FPET, as well as informative visuals for use in consensus meetings with government stakeholders. This approach ensures that existing workflows remain intact while incorporating the advancements required to handle the more complex EMU calculation process (Mooney et al. [2024a]).

By complementing the current practices of M&E officers and aligning with their existing skills and training, `ss2emu` offers a practical, reproducible, and scalable solution for calculating EMU with uncertainty. This package supports a range of stakeholders, including technical officers, researchers and policymakers, by enhancing the modelling efforts in family planning programs.

The rest of this paper is structured as follows: we begin with background, followed by a section discussing the evolution of the use of service statistics in FPET, we then present an overview of the core functions and workflow of `ss2emu`, and conclude with a final discussion.

4.2 Background

4.2.1 Service statistics and Estimated Modern Use

Family planning service statistics are collected at the facility level as part of routine service delivery, typically through Health Management Information Systems (HMIS) such as DHIS2 (DHIS2). These statistics include four types of data: the number of contraceptive commodities distributed to clients and facilities, the number of family planning visits to a facility, and the number of family planning users registered at a facility. To analyse contraceptive use at a national level, these service statistics are aggregated and converted into EMUs.

4.2.1.1 Track20 Project and SS-to-EMU Tool

The Track20 project (https://www.track20.org/) empowers countries to build the skills and systems for effective family planning data collection and analysis. Track20 trains family planning in-country Monitoring and Evaluation (M&E) officers, who serve as data experts responsible for managing and reviewing family planning statistics. The project promotes ownership of country-level data and enhances local capacity through annual workshops, where M&E officers are trained to collate and transform service statistics into EMU.

As part of their work, M&E officers use the SS-to-EMU tool, developed by Track20, to convert aggregated service statistics into EMUs. This tool incorporates several inputs, such as country, language, service statistics types, data sources, annual quantities of each contraceptive method, details of the family planning facility sectors and facility types that are contributing data, and reporting rates. The tool provides analyses and visualisations of service statistics, allowing for data quality review via benchmarking of indicators, such as method mix, which describes the annual distribution of contraceptive methods (Data For Impact [c]). Figure 4.1 illustrates an example of visualisations provided in the tool. The left figure highlights trends in the number of users of each contraceptive method in the data. The right figure shows the comparison of the observed method mix from service statistics data against the expected method mix based on survey data. Visualisations such as these enable a thorough review of data quality, helping to identify outlying observations and gaps in the data.

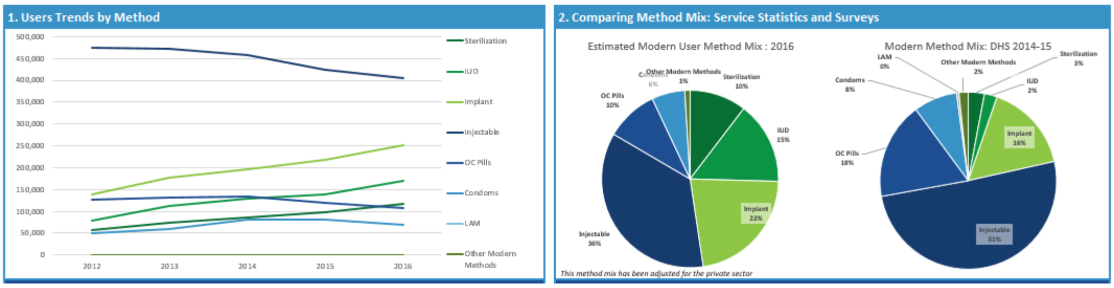


Figure 4.1: Example plots provided in the SStoEMU tool when reviewing service statistics. (a) User trends by contraceptive method over time. (b) Comparison of method mix observed from service statistics and survey data. Obtained from Track20 [2024].

Once the data is processed, EMUs are derived, representing the annual proportion of modern contraceptive users. This data is then considered for use in FPET to obtain annual estimates and short-term forecasts of mCPR. This is discussed further in Section 4.2.2.

4.2.1.2 Overview of the SS-to-EMU process

Contraceptive services are provided by both public and private facilities, but contributions from the private sector (e.g., NGOs, private hospitals, clinics, pharmacies) are often underreported (Magnani et al. [2018]). To ensure EMUs reflect the entire contraceptive market, a private sector adjustment factor is applied. This factor accounts for facility representation and contraceptive supply share, i.e., the proportion of each method provided by different facility types (Data For Impact [d]). Recent advancements in EMU calculation have integrated a Monte Carlo-based uncertainty approximation into the private sector adjustment step (Mooney et al. [2024a]). However, the computational demands of the Monte Carlo approximation exceed the capacity of the excel-based SS-to-EMU tool. To address this, the method was implemented using the proposed R package (R Core Team [2021]).

The EMU calculation, including the private sector adjustment, that is implemented in the R package is summarised below.

For each sample j, the adjusted number of users in country c in service statistics type s of contraceptive method m at time t is given by:

$$\eta_{c,s,t,m,j} = \lambda_{c,s,t,m,j}\theta_{c,s,t,m}, \tag{4.1}$$

where $\theta_{c,s,t,m}$ is the initial estimated number of users of contraceptive method m derived from service statistics type s and $\lambda_{c,s,t,m,j}$ is the private sector adjustment factor, which scales up $\theta_{c,s,t,m}$ to account for missing private sector contributions. Further details on obtaining the initial estimated number of users ($\theta_{c,s,t,m}$) is provided in Section 4.3.3.

The private sector adjustment factor is calculated as:

$$\lambda_{c,s,t,m,j} = \frac{1}{\sum_{f=1}^{F} \tau_{c,s,f,j}\beta_{c,t,m,f,j}}. \tag{4.2}$$

where $\tau_{c,s,f,j}$ represent the j^{th} sample of the facility reporting level factor, which quantifies the level of contribution of facility type f in country c, in service statistics type s and $\beta_{c,t,m,f,j}$ refers to the j^{th} sample of contraceptive supply share, representing the proportion of method m supplied by facility type f.

The annual estimated number of users for each contraceptive method is summed across all methods to generate a total estimate of modern contraceptive users. This total is then expressed as a proportion of the population of women of reproductive age, providing EMU.

The updated approach generates samples of the number of users for each contraceptive method, resulting in EMU samples. For a given country c, service statistics type s, and time t, the estimated number of users for contraceptive method m for sample j is denoted as $\eta_{c,s,t,m,j}$. The EMU, $z_{c,s,t,j}$, is then calculated as:

$$z_{c,s,t,j} = \frac{\sum_{m=1}^{M} \eta_{c,s,t,m,j}}{q_{c,t}}, \tag{4.3}$$

where M is the total number of contraceptive methods and $q_{c,t}$ represents the population of women of reproductive age in country c at time t, and j denotes the sample iteration. Population data is sourced from the United Nations Population Division (United Nations Population Division [a]).

The point estimate of EMU is given by the median of $z_{c,s,t,1:J}$ for each country, type, and year, while uncertainty is quantified using the standard deviation of the samples. While this refinement incorporates uncertainties associated with specific calculation inputs, it also maintains EMU point estimates from the SS-to-EMU tool. This approach quantifies the uncertainty in the EMU while ensuring that the point estimates remain aligned with the outputs of the SS-to-EMU tool.

4.2.2 Family Planning Estimation Tool (FPET)

The Family Planning Estimation Tool (FPET) produces country-level estimates using survey data and service statistics data in the form of EMUs as input into a Bayesian hierarchical model to estimate and project mCPR over time (Alkema et al. [2013], New et al. [2017], Cahill et al. [2018], Kantorová et al. [2020], Alkema et al. [2024c]). The survey data model captures assumptions regarding how survey data relate to the true family planning indicators, while also accounting for various errors associated with the data. The EMU data model, which is implemented alongside the survey data model, defines the relationship between EMUs, specifically rates of change in EMUs and rates of change in true mCPR (Magnani et al. [2018], Cahill et al. [2021], Mooney et al. [2024b]).

The most recent update to the EMU data model incorporates a Bayesian hierarchical approach that uses annual EMU rates of change as input, decomposing uncertainty into two components: observation-specific uncertainty and country-type uncertainty (Mooney et al. [2024b]). The country-type uncertainty is estimated hierarchically, with hyperparameters derived from training data across all countries.

This update improved the quantification of uncertainty in the EMU data model, allowing it to better capture country-specific contexts, leading to more influence on mCPR estimates where EMUs are considered high quality. For example, Figure 4.2 illustrates country-level mCPR estimates and projections obtained using the survey-only model, vs the survey+EMU model (using both surveys and EMUs as input), for MWRA, UWRA and AWRA, in order to highlight the impact of including EMUs in FPET on estimates and projections. In this example, the most recent survey was conducted in 2018, while EMU data is available annually up to 2022. The recent upward trend in EMUs leads to higher mCPR estimates after 2018 compared to those generated by the survey-only model.

These updates highlight the importance of including EMUs with observation-specific uncertainty in FPET. By doing so, we can improve mCPR estimates, especially in cases where EMUs provide high-quality data that makes projections more reliable.

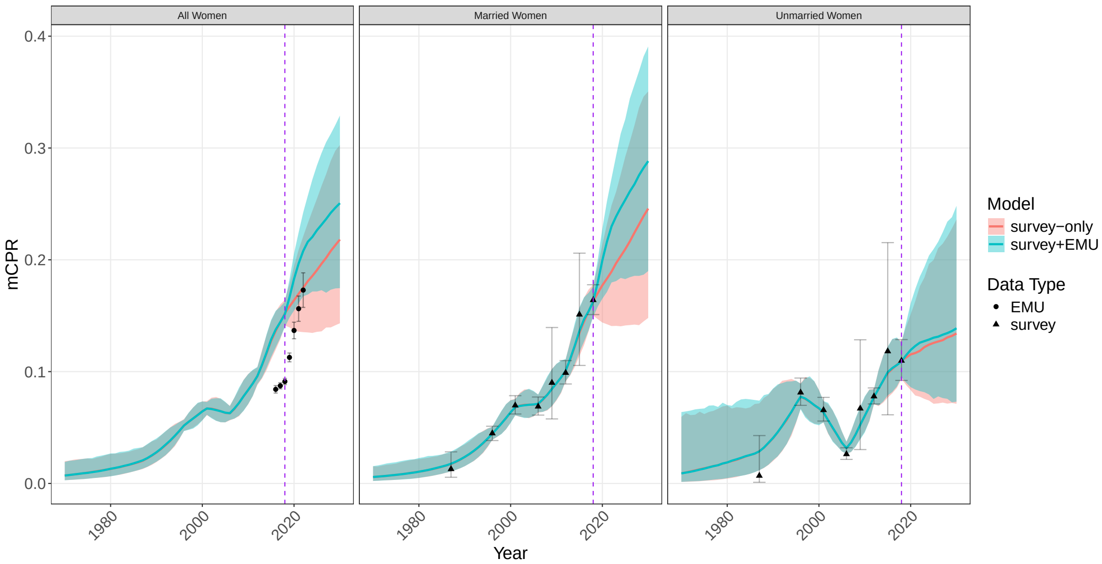


Figure 4.2: Example of country-level FPET estimates of mCPR for MWRA, UWRA and AWRA, obtained using the survey-only model and survey+EMU model. Solid lines indicate median estimates of mCPR, shaded regions show the 95% credible intervals. Results in red highlight the use of the survey-only model. Results in blue highlight the use of surveys and EMU. The error bars represent the 95% confidence interval associated with the data. The purple dashed line marks the year of the most recent survey.

4.3 Computational advancements with an R package

The `ss2emu` package was developed to perform the most advanced SS-to-EMU calculation in R (R Core Team [2021]). The package integrates into previously established workflows, enabling users to input data, calculate EMU, and produce visualisations efficiently while ensuring accessibility by producing outputs in both English and French, depending on the input data. This supports its use in many country contexts and ensures accessibility for a wide range of users.

4.3.1 Installation

ss2emu is an open-source R package stored on GitHub (https://github.com/shaunamooney/ss2emu) and can be installed using the devtools package (Wickham et al. [2022]).

```
install.packages("devtools")
devtools::install_github("shaunamooney/ss2emu")
```

4.3.2 Data

The ss2emu package includes three pre-loaded datasets, designed to facilitate the calculation of EMU from service statistics. Each dataset is described below with example tables.

1. **Annual Modelled Contraceptive Supply Share Estimates.** This dataset, named fp_source_data_wide, contains annual estimates of contraceptive supply shares for different countries, broken down by each family planning facility type, derived from Demographic and Health Surveys (DHS) (The DHS Program [a]). Table 4.1 provides a sample of this dataset.

2. **Annual Contraceptive Supply Share Uncertainty Estimates.** This dataset, referred to as supply_share_sd, provides uncertainty estimates, in the form of standard deviations, for the annual contraceptive supply estimates. These estimates are derived from model-based output of supply share estimates with uncertainty (Comiskey et al. [2024, 2023]). Table 4.2 illustrates an example of this dataset. Comiskey et al. [2024] model the logit-transformed proportions of the public-sector supply share and the ratio of private sector to the non-public sector using a Bayesian hierarchical penalized spline approach. The uncertainty in these estimates is summarized by the standard deviations of the posterior samples, referred to as sd_logit_pub and sd_logit_priv_ratio in Table 4.2.

3. **Country Code Data.** The country code dataset, named country_code_data, provides a unique numeric code to each country, three-digit numerical codes used for statistical processing by the United Nations Statistics Division (UN

Statistics Division [2021]). These codes ensure consistency as they are also used in FPET.

name	year	method_overview	Public Sector	NGO	Private Hospital/Clinic	Pharmacy	Shop/Church/Friend	Other
Kenya	2003	Condom (M)	0.16	0.00	0.09	0.18	0.56	0.01
Kenya	2004	Condom (M)	0.18	0.00	0.07	0.17	0.56	0.01
Kenya	2005	Condom (M)	0.19	0.00	0.06	0.17	0.56	0.02

Table 4.1: Sample table of annual modelled contraceptive supply share estimates. The column `name` provides the country name, `year` indicates the year, and `method_overview` specifies the contraceptive method type. The column `Public Sector` shows the proportion of contraceptives supplied by the public sector, while `NGO`, `Private Hospital/Clinic`, `Pharmacy`, `Shop/Church/Friend` and `Other` display the proportions supplied by various private sector facility types.

name	year	method_overview	sd_logit_pub	sd_logit_priv_ratio
Kenya	2003	Implants	0.22	1.80
Kenya	2004	Implants	0.23	1.80
Kenya	2005	Implants	0.25	1.79

Table 4.2: Sample data from the annual contraceptive supply share uncertainty estimates dataset. The column `name` provides the country name, `year` indicates the year, and `method_overview` specifies the contraceptive method type. The column `sd_logit_pub` shows the standard deviation of the logit for the public sector supply share, while `sd_logit_priv_ratio` represents the standard deviation of the logit for the private sector to the non-public sector.

4.3.3 ss2emu workflow

The `ss2emu` package is designed around a structured three-step workflow: data extraction, EMU calculation, and visualisation. Each of these steps is discussed in detail in the following sections. Figure 4.3 provides an overview of the workflow implemented in the package.

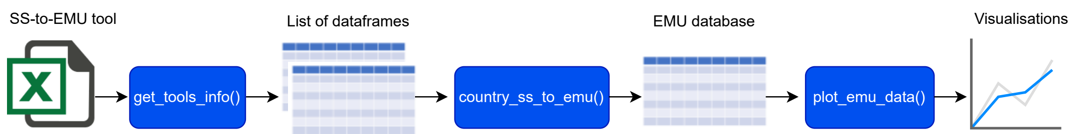


Figure 4.3: Overview of the `ss2emu` workflow. Blue boxes denote the primary functions provided by the package.

Input data

The `get_tools_info()` function acts as the first step, extracting necessary input data from the SS-to-EMU tool. A summary of each parameter used in the function is provided in Table 4.3. This function organises the input data for subsequent calculations.

Users input the file path for the SS-to-EMU tool and specify the type of service statistics data to be calculated, typically the data intended for use in FPET. The function then retrieves the relevant data from each sheet of the SS-to-EMU tool, including:

- Service statistics (annual quantities of commodities, visits or users of each contraceptive method).
- Country-specific annual population data.
- Country details, including language and whether data refers to all women or only married women of reproductive age.
- Reporting level of each type of family planning facility.
- Annual reporting rates.
- Couple Years of Protection (CYP) factors.
- Method-specific continuation rates.
- User-inputted data dictating whether the private sector adjustment should be applied to each contraceptive method.
- Inclusion of condoms in the EMU calculations.
- Annual model-based estimates of mCPR obtained from FPET.

Supporting both English and French versions of the tool, the function ensures wide applicability across different regions. It returns the aforementioned data frames in the form of a list.

Argument	Data Type	Description
`country_file_path`	`character`	The file path to the country's SS-to-EMU Excel spreadsheet.
`input_type`	`character`	The chosen service statistics type to calculate. Options are as follows: "clients" (commodities distributed to clients), "facilities" (commodities distributed to facilities), "visits" (family planning visits), and "users" (family planning users).

Table 4.3: Parameter details for the `get_tools_info` function.

Sampling & EMU calculation

The second step in the workflow involves the EMU calculation, which is carried out by the `country_ss_to_emu()` function. Each parameter used in the function is summarised in Table 4.4. Using the data extracted in the first step, this function implements a sampling based approach to produce EMUs with uncertainty.

In Section 4.2.1.2, we outlined the process of calculating EMU using service statistics and the application of a private sector adjustment factor. This section details the implementation of these steps in the `country_ss_to_emu()` function, which uses a sampling-based approach to calculate EMUs with uncertainty.

First, annual user counts for each contraceptive method are estimated, denoted as $\theta_{c,s,t,m}$ in Equation 4.1, as previously defined in Section 4.2.1.2. Short-term methods (STMs) and long-acting and permanent methods (LAPMs) are processed separately. For STMs, data on commodities distributed and family planning visits are converted into user estimates using Couple Years of Protection (CYP) factors, which quantify the contraceptive coverage provided by a single unit or visit of each method (U.S. Agency for International Development).

In country c, for service statistic type s at time t, and contraceptive method m, let $\theta_{c,s,t,m}$ represent the number of users. Let $x_{c,s,t,m}$ denote the observed quantities, and $\kappa_{m,s}$ be the CYP factor for method m based on service statistics type s. Where

m is an STM, the number of users is calculated as:

$$\theta_{c,s,t,m} = x_{c,s,t,m} \cdot \frac{1}{\kappa_{m,s}}. \tag{4.4}$$

Since LAPMs provide protection over multiple years, users must be accounted for across time. The total number of LAPM users includes new users in a given year, continuing users from previous years, and historic users, who received a method before data collection began but whose protection still extends into the current year. Historic and continuing LAPM users are estimated using method-specific continuation rates, allowing the continuity of a method to influence how many users from previous years carry through into the current year (Data For Impact [a]).

For a LAPM, the total number of users in country c, captured by service statistics type s, at time t, for method m is calculated as:

$$\theta_{c,s,t,m} = u_{c,s,t,m} + h_{c,s,t,m}, \tag{4.5}$$

where $\theta_{c,s,t,m}$ represents the total number of LAPM users in country c for method m in year t and service statistics type s. The variable $u_{c,s,t,m}$ indicates the recorded number of users (new and continuing) in country c for method m in year t and service statistics type s. The term $h_{c,s,t,m}$ denotes the historic number of users in country c for method m in year t and service statistics type s.

The number of recorded number of users is given by:

$$u_{c,s,t,m} = \sum_{k=0}^{t-t_0} \left(x_{c,m,t-k,s} \cdot \alpha_{m,k+1} \right), \tag{4.6}$$

where $u_{c,s,t,m}$ represents the total number of recorded users for country c, method m, year t, and data type s. The variable $x_{c,s,t,m}$ refers to the new users for country c, method m, year t, and data type s. The continuation rate for method m after k years of use is denoted by $\alpha_{m,k}$. Finally, t_0 signifies the first year of data collection.

The number of historic users is calculated as:

$$h_{c,s,t,m} = \sum_{k=t-t_0}^{16} \left(x_{c,m,t_0,s} \cdot \alpha_{m,k} \right) \cdot \gamma_{c,m}, \tag{4.7}$$

where $h_{c,s,t,m}$ represents the historic number of users in country c for method m in year t and service statistics type s, $x_{c,m,t_0,s}$ refers to the number of observed users in country c for method m for the first year of recorded data, and $\gamma_{c,m}$ is the scaling factor specific to country c for method m, defined as:

$$\gamma_{c,m} = \begin{cases} 1 & \text{if method } m \text{ in country } c \text{ was consistently available in the past,} \\ 0.5 & \text{if method } m \text{ in country } c \text{ was scaling up in use,} \\ 0 & \text{if method } m \text{ in country } c \text{ was newly introduced in year } t_0. \end{cases} \tag{4.8}$$

Next, in order to account for any partially or fully missing private sector facilities from service statistics, we adjust annual user counts of each contraceptive method using the private sector adjustment. This involves calculating a scale-up factor, known as the private sector adjustment factor, as defined in Equation 4.2. The adjustment factor is based on two key pieces of information: model-based estimates of the proportion of each contraceptive method supplied by different types of facilities, known as contraceptive supply share (as detailed in Tables 4.1 and 4.2), and the extent to which these facilities are represented in the data (each facility type is classified as fully, partially, or non-reporting). A Monte Carlo approximation, a sampling-based approach, is used to generate samples of the private sector adjustment factor by accounting for the uncertainty in its inputs, as defined in Equation 4.1. When these samples of the adjustment factor are applied to the annual user counts, we obtain samples of adjusted user counts for each contraceptive method.

Finally, the adjusted user counts are aggregated to produce samples of the annual estimate of modern contraceptive users. These samples are then expressed as a proportion of women of reproductive age to calculate EMU samples, as shown in Equation 4.3. This allows for the quantification an EMU point estimate along with observation-level uncertainty. Further details can be found in Mooney et al. [2024a]

This step represents the core computational component of the package, transforming service statistics data into EMUs. The output of this function is a list containing multiple data frames, the key one being the a database of EMUs.

Argument	Data Type	Description
`country_tools_info`	`list`	The country tools information, contained in the output from `get_tools_info()`.
`input_type`	`character`	The chosen service statistics type.
`method_summary`	`logical`	Whether to summarize by contraceptive method (`TRUE`) or not (`FALSE`). Default is FALSE.
`save_samples`	`logical`	Whether to save samples for further analysis (`TRUE`) or not (`FALSE`). Default is FALSE.

Table 4.4: Parameter details for the `country_ss_to_emu` function.

Visualisation

The final function in the workflow focuses on visualisation using the `ggplot2` package (Wickham [2016]). The `plot_emu_data()` function generates clear and informative visualisations, highlighting trends in EMU with uncertainty and model-based estimates of mCPR derived from FPET. This helps users benchmark EMUs against survey-informed mCPR and better understand how uncertainty evolves over time. The function tailors the outputs to the language of the input tool, providing visualisations in either English or French, depending on the language of the input data.

Argument	Data Type	Description
`emu_data`	`data.frame`	A table containing EMUs for chosen data type, contained in the output of `country_ss_to_emu`.
`mcpr_data`	`data.frame`	A table containing mCPR model-based estimates, contained in the output of `country_ss_to_emu`.

Table 4.5: Parameter details for the `plot_emu_data` function.

The `ss2emu` package is designed to be modular, with each function serving a specific purpose within the workflow. This approach allows users to easily follow the process, from data extraction to visualisation, making it user-friendly and easy to integrate into existing workflows.

4.3.4 Implementation

We demonstrate the implementation of the `ss2emu` workflow using an anonymised country case study. We use `get_tools_info()` to extract relevant input data from the completed SS-to-EMU tool file.

```
input_data <- get_tools_info(
    country_tool_filepath = "~/SS-to-EMU_example.xlsx",
    input_type = "clients")
```

The extracted data is stored as a list containing various data frames required for EMU calculations. An example of accessing the data stored in `input_data` is shown below.

```
print(input_data$ss_quantity_data)

# A tibble: 22 × 13
   ss_type         method_detail      `2012` `2013` `2014` `2015` `2016`
   <chr>           <chr>               <dbl>  <dbl>  <dbl>  <dbl>  <dbl>
 1 Contraceptiv... Tubal Ligati...     NA     NA     NA     NA     NA
 2 Contraceptiv... Vasectomy (M)       NA     NA     NA     NA     NA
 3 Contraceptiv... Copper- T 38...     8721  11622  11018  11630   9602
 4 Contraceptiv... LNG-IUS             NA     NA     NA     NA     NA
 5 Contraceptiv... Implanon            NA     NA     NA     NA     NA
 6 Contraceptiv... Sino-Implant        NA     NA     NA     NA     NA
 7 Contraceptiv... Jadelle             NA     NA     NA     5022  15156
 8 Contraceptiv... Depo Provera...   90787 105874  98346  94103  92769
# 14 more rows
# 4 more variables: `2017` <dbl>, `2018` <dbl>, `2019` <dbl>,
#  `2020` <dbl>, `2021` <dbl>, `2022` <dbl>
```

The `country_ss_to_emu()` function processes the input data and calculates EMU. This produces a dataset containing EMUs with uncertainty, ready for analysis or visualization. The dataset contains several key columns: `division_numeric_code`, which represents the country or region as a numeric code; `name`, indicating the name of the country; `pop_type`, specifying whether the EMUs are collected for all women (AW) or married women (MW); and `ss_type`, which describes the type of service statistics data. It also includes `year`, denoting the observation year; `emu`, representing the EMU; `emu_roc`, indicating the EMU-based rate of change; `sd_emu`, providing the standard deviation of the EMU and gives insight into the uncertainty associated with the EMU; and `sd_emu_roc`, showing the standard deviation of the EMU-based rate of change, similarly reflecting the uncertainty associated with the EMU-based rate of change. Additionally, the dataset includes the `Region` column, which specifies the subnational region name for subnational EMUs if the tool contains subnational data. Example code is shown below.

```
emu_output <- country_ss_to_emu(
    country_tools_info = input_data,
    input_type = "clients")

emu_dataset <- emu_output$emu_dataset

print(emu_dataset)

# A tibble: 11 × 10
# Groups:   division_numeric_code, name, pop_type, ss_type [1]
   div_numeric_code name   pop_type ss_type  year    emu   emu_roc  sd_emu
               <dbl> <chr>  <chr>    <chr>  <dbl>  <dbl>     <dbl>    <dbl>
 1                 -    -       AW       clients  2012 0.0577 NA        0.00446
 2                 -    -       AW       clients  2013 0.0560 -0.00178 0.00384
 3                 -    -       AW       clients  2014 0.0495 -0.00643 0.00319
 4                 -    -       AW       clients  2015 0.0478 -0.00173 0.00256
 5                 -    -       AW       clients  2016 0.0489  0.00112 0.00182
 6                 -    -       AW       clients  2017 0.0523  0.00334 0.00140
```

```
 7              -    -      AW        clients   2018 0.0613   0.00904 0.00135
 8              -    -      AW        clients   2019 0.0732   0.0119  0.00171
 9              -    -      AW        clients   2020 0.0810   0.00784 0.00222
10              -    -      AW        clients   2021 0.0980   0.0170  0.00328
11              -    -      AW        clients   2022 0.114    0.0157  0.00494
# 2 more variables: sd_emu_roc <dbl>, Region <lgl>
```

We use `plot_emu_data()` to visualise the trends in EMUs, and compare them to model-based mCPR estimates from FPET. The resulting plot highlights the uncertainty in EMUs and compares with survey-informed mCPR estimates, as seen in Figure 4.4, which illustrates an anonymised country-level output. The plot contains two visualisations: one visualising EMU with uncertainty over time, and the second visualising EMU rates of change with uncertainty over time. Both visuals include model-based mCPR over time obtained from FPET for comparison. These visualisations provide insights into the assessing the ability of EMUs to track trends in mCPR. The inclusion of uncertainty acknowledges inherent variability in estimates due to the derivation process, helping to assess the reliability of each observation. Figure 4.4 highlights variations in observation-level uncertainty over time and demonstrates that the rate of change in EMUs consistently shows steeper increases or decreases compared to survey-informed mCPR estimates. Each plot is accompanied by detailed captions, which provide context to help users interpret the results, making the outputs especially useful for non-technical audiences.

```
fpet_mcpr <- input_data$fpet_mcpr_data
emu_plot <- plot_emu_data(emu_dataset, fpet_mcpr)
print(emu_plot)
```

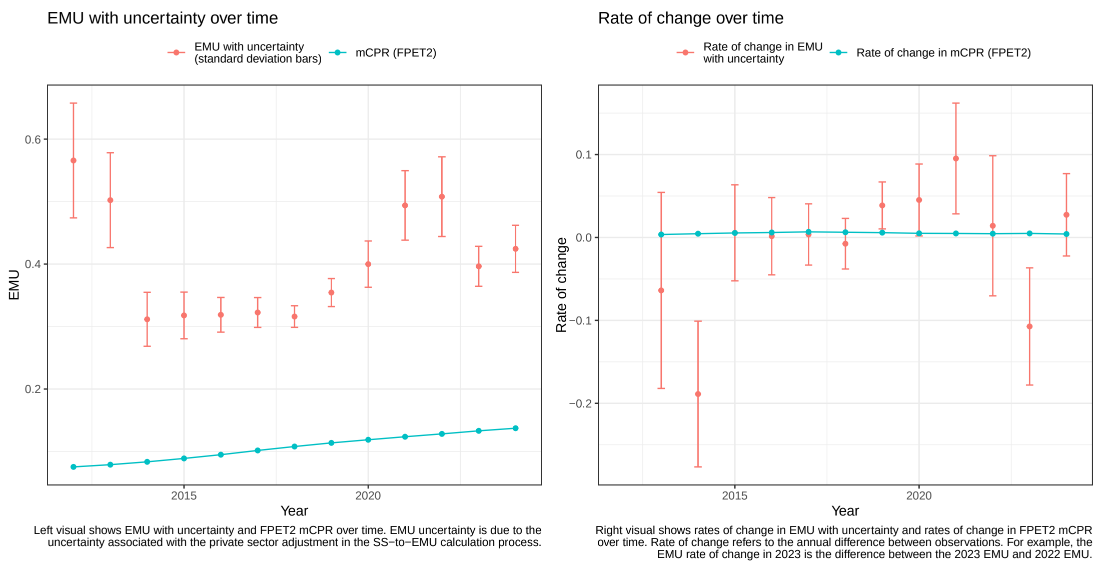


Figure 4.4: Example output obtained using the `plot_emu_data()` function. Vertical error bars represent uncertainty. (a) visualises EMUs with uncertainty over time, coloured in red, along with model-based estimates of mCPR obtained from FPET, coloured in blue. (b) visualises EMU-based rates of change, coloured in red, and rates of change observed in model-based mCPR, coloured in blue.

4.3.5 Shiny App

Shiny is an open-source web application framework for R, which allows users to build interactive web apps directly from R (Chang et al. [2024]). In this section, we describe the Shiny application that integrates with the `ss2emu` package to facilitate the calculation of EMUs.

The Shiny application built with the `ss2emu` package (avenirhealth.shinyapps.io/SStoEMUShiny/) offers a user-friendly interface for users to calculate and visualise EMUs with observation-level uncertainty. It extends the functionality of the `ss2emu` R package by providing a simple web-based interface that is easy to use and accessible to both technical and non-technical users. Figure 4.5 shows the Shiny app interface.

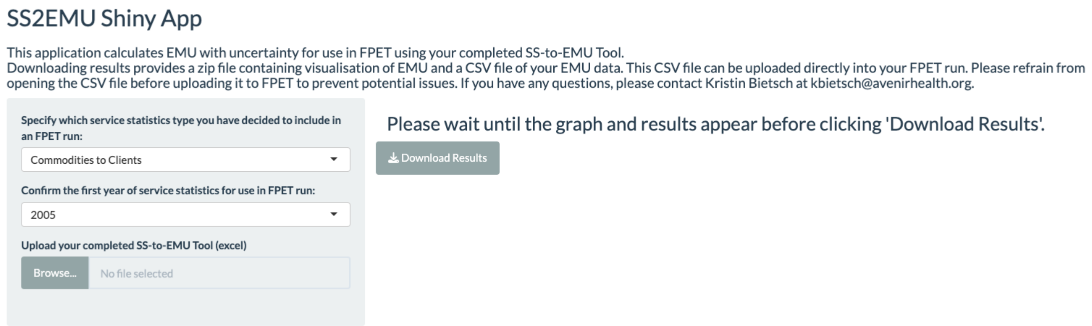
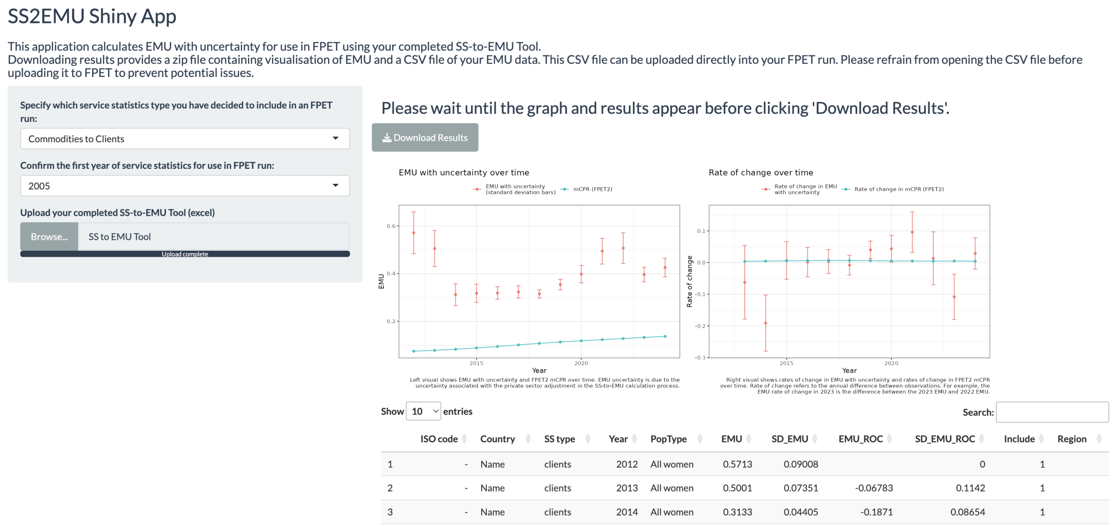


Figure 4.5: A screenshot of the user interface for Shiny App, where the user chooses the service statistics type intended to be used in FPET, along with the first year of data that is intended to be included. Subsequently, the user can upload their completed SS-to-EMU tool and await results.

The primary purpose of the Shiny App is to process a completed SS-to-EMU tool and calculate EMUs, along with rates of change and associated uncertainties. Users begin by providing three key inputs: the chosen type of service statistics data, the completed SS-to-EMU tool, and, optionally, a filter to limit the analysis to data after a specified year. The filtering option is useful for countries that may have experienced some volatility in their data collection systems, such as transitioning from a paper-based system to an HMIS, and wish to exclude those years from the output.

Once the required data is uploaded, and calculation is complete, users can view the visualisations, as previously illustrated in Figure 4.4. Plots are automatically generated in the language of the uploaded SS-to-EMU tool, ensuring that the visualisations are accessible to a wider range of users. Figure 4.6 illustrates an example of the outputs obtained after uploading the required data.



	ISO code	Country	SS type	Year	PopType	EMU	SD_EMU	EMU_ROC	SD_EMU_ROC	Include	Region
1	-	Name	clients	2012	All women	0.5713	0.09008		0	1	
2	-	Name	clients	2013	All women	0.5001	0.07351	-0.06783	0.1142	1	
3	-	Name	clients	2014	All women	0.3133	0.04405	-0.1871	0.08654	1	

Figure 4.6: A screenshot of the output of the Shiny App after uploading required data. The output shows EMU visualisations and an EMU database, both available for download by clicking the "Download Results" button.

In addition to the visualisations, the app outputs an EMU database, formatted for direct use in FPET. An example of this database is illustrated in Figure 4.7. This database can be uploaded directly in FPET to inform estimates and forecasts of mCPR, as illustrated in Figure 4.2. This table, along with the plots, can be downloaded as a compressed ZIP file, allowing users to access the data offline or use it for further analysis. The overall workflow of using service statistics to derive EMU using `ss2emu` and subsequently using the output to inform estimates of mCPR in FPET is illustrated in Figure 4.8.

	ISO code	Country	SS type	Year	PopType	EMU	SD_EMU	EMU_ROC	SD_EMU_ROC	Include	Region
1	-	Name	clients	2012	All women	0.5713	0.09008		0	1	
2	-	Name	clients	2013	All women	0.5001	0.07351	-0.06783	0.1142	1	
3	-	Name	clients	2014	All women	0.3133	0.04405	-0.1871	0.08654	1	
4	-	Name	clients	2015	All women	0.3189	0.03734	0.006411	0.05862	1	
5	-	Name	clients	2016	All women	0.3176	0.02838	-0.0005659	0.04788	1	
6	-	Name	clients	2017	All women	0.3241	0.02538	0.005646	0.0387	1	
7	-	Name	clients	2018	All women	0.3149	0.01783	-0.00747	0.03135	1	
8	-	Name	clients	2019	All women	0.3549	0.02172	0.04012	0.02812	1	
9	-	Name	clients	2020	All women	0.3987	0.03657	0.0433	0.04263	1	
10	-	Name	clients	2021	All women	0.4955	0.05191	0.09748	0.0632	1	

Figure 4.7: A screenshot of the EMU database obtained from the Shiny app. The database can be uploaded directly in FPET to use service statistics when estimating mCPR.

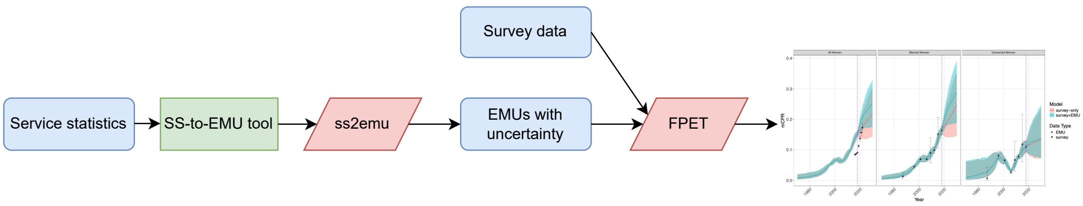


Figure 4.8: Overall workflow implemented when using service statistics to derive EMUs and use in family planning modelling. Service statistics are inputted into an SS-to-EMU tool, which is then used as input data for the `ss2emu` R package. The package extracts relevant data and calculates EMUs with uncertainty. Survey and EMU data are inputted into FPET which produces estimates and short-term forecasts of mCPR with uncertainty.

Overall, the Shiny App enhances the functionality of the `ss2emu` package by offering an interactive and accessible platform for generating EMUs with uncertainty. This ensures that enhancements in the EMU calculations are scalable and accessible to all stakeholders, both technical and non-technical.

4.4 Discussion

In this paper we presented the `ss2emu` R package. While existing tools for deriving EMUs from service statistics were reliable, the increasing complexity of modelling efforts has created a need for scalable and reproducible solution to deriving EMUs with uncertainty. `ss2emu` addresses this gap by enabling the calculation of EMU from service statistics in R in a fully reproducible manner (R Core Team [2021]). We discussed it's value in facilitating the calculation of EMU using the most up to date methods, whilst complementing domain knowledge and training in terms of the familiarity of family planning data experts with existing tools.

A key strength of `ss2emu` is its compatibility with the widely used SS-to-EMU tool, integrating seamlessly into existing workflows. This integration ensures that Monitoring and Evaluation officers in low- and middle-income countries can continue using familiar workflows while accessing more advanced capabilities. By building on established tools, `ss2emu` fosters user confidence and ensures widespread use. We highlight the value in the use of the already established tool for data compilation and quality review, whilst complementing it with a reproducible step to ensure no errors have occurred during data entering.

`ss2emu` benefits a broad range of users. A key feature of `ss2emu` is its simple workflow. The R package is aimed at technical users, such as researchers and technical officers, but the straightforward and intuitive workflow also makes it accessible to less-technical users with minimal training. In addition, the Shiny app provides a user-friendly web interface for use by those not familiar with coding, without the need for extensive additional training. By ensuring the package can handle both English and French data input, as well as provide visualisations in both English and French, we ensure accessibility to all users.

A central goal of family planning modelling efforts is to promote the use of country-tools to ensure ownership of estimates, and empower in-country data analysis and evaluation of family planning data. This approach is reflected in the development of the Family Planning Estimation Tool (Alkema et al. [2024c]). When using cross-collaboration across domain knowledge - it is essential to work with reproducibility for all users in mind. `ss2emu` moves us closer to this goal by ensuring the transformation from service statistics to EMU is performed in both a reproducible and accessible way.

In future, `ss2emu` will make it easier to implement any further enhancements to EMU calculations. As modelling efforts evolve and new methods are developed, the package can be easily adapted to incorporate any improvements. This ensures that the package remains scalable and flexible, allowing for the introduction of updated techniques with minimal disruption to existing workflows.

The work discussed in this paper has implications for evidence-based decision-making in family planning policy. By providing a scalable and reproducible approach to calculating EMU with uncertainty, `ss2emu` allows data experts to make more informed decisions, particularly when considering associated uncertainty with EMUs. The inclusion of uncertainty in the calculations strengthens the reliability of these estimates, highlighting the inherent variability associated with each EMU. This is especially crucial in low- and middle-income countries, where accurate monitoring of family planning indicators is essential for tracking progress. The tool's ability to facilitate the integration of uncertainty into EMU calculations enhances decision making, ensuring it is based on the most accurate and up-to-date data.

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Conflicts of interest

There are no conflicts of interests to declare.

CHAPTER 5

Conclusions

This thesis has introduced significant advancements in the calculation, modelling, and implementation of Estimates of Modern Use (EMU) from family planning service statistics (Track20 [2020]). Across three main chapters, we have enhanced the accuracy, usability, and impact of EMUs by integrating uncertainty quantification, improving the EMU data model in the Family Planning Estimation Tool (FPET), and developing a reproducible software tool. Collectively, these contributions strengthen the role of EMUs in tracking modern contraceptive prevalence (mCPR) and support family planning monitoring efforts, particularly in data-scarce settings.

Chapter 2 introduced an updated approach to EMU calculation, addressing uncertainty in the private sector adjustment process. This work represents a shift away from reliance on point estimates and marks the first time observation-level uncertainty in this indicator has been quantified. By allowing the private sector adjustment factor to vary over time and incorporating uncertainty in its inputs, this approach provides a more accurate and informed representation of contraceptive use than the previous fixed-factor method. The case studies demonstrated how these enhancements influence EMU point estimates and trends, and emphasise the importance of accounting for inherent uncertainty in EMU calculations. This was particularly evident as the resulting private sector adjustment factors varied over time in both point estimates and uncertainty, directly influencing resulting EMUs.

The incorporation of uncertainty in EMU rates of change in this work further highlights the potential of EMU as a supplementary data source for FPET, which relies on EMU rates of change as input (Cahill et al. [2021]). By considering uncertainty, we achieve a more accurate representation of this indicator, therefore enhancing the reliability of EMU in informing mCPR estimates.

While this work focused on national EMU data, future research could expand these methods to subnational EMU calculations. Currently, subnational EMUs rely on national contraceptive supply share estimates during the private sector adjustment process. However, supply share estimates at the subnational level are available (Comiskey et al. [2023]). Incorporating these estimates would improve the accuracy of EMU calculations at the subnational level and provide more detailed insights for family planning programs.

Building on the work in Chapter 2, Chapter 3 introduced an updated EMU data model framework to inform mCPR estimates and forecasts within FPET in the absence of recent survey data. This work introduced EMU observation-specific uncertainty into FPET for the first time, ensuring that data with greater uncertainty had less influence on mCPR estimates and projections. This framework also decomposed EMU uncertainty in FPET for the first time and accounted for country-type-specific uncertainty, addressing previous issues with over-inflated uncertainty from certain EMU data types being incorporated the country level (Cahill et al. [2021]). Out-of-sample validation confirmed that this approach improved predictive accuracy for both married and unmarried women, with significant impacts in data-sparse settings.

Future work could explore the inclusion of a bias term in the model to assess whether certain service statistics data types tend to consistently overestimate or underestimate mCPR. Incorporating such a term would allow the model to adjust for systematic biases, potentially improving the accuracy of estimates and forecasts. In addition, future work could explore the use of covariates to better assess EMU quality when integrating them into FPET, providing further insights into the reliability of the data used for mCPR estimates. Covariates could include annual reporting rates, which represent the proportion of facilities reporting data relative to the expected number (Maïga et al. [2019]). Currently, reporting rates for family planning service statistics are only used as a threshold for EMU calculation, reporting must be at least 60% in a given year for an EMU observation to be included. Incorporating reporting rates as a covariate could help account for differences in data completeness that could impact data reliability.

Finally, Chapter 4 introduced `ss2emu`, an R package designed to perform SS-to-EMU calculations. By generating EMUs directly from service statistics in R, this tool enhances the reproducibility of the indicator while addressing the limitations of the Excel-based SS-to-EMU approach (Track20 [2023]). It also integrates smoothly into existing workflows used by family planning data experts. The addition of the Shiny app further enhances accessibility, extending use to non-technical users.

Reproducibility is a core principle in the family planning modelling community, as seen in the adoption of in-country, open-source tools such as FPET (Alkema et al. [2024c]). Coupled with the ongoing technical support provided by the Track20 project, these efforts contribute to local capacity building and empower governments with country-led assessments of key indicators. In this context, `ss2emu` aligns with and advances these principles, further promoting transparent, reproducible, and locally led data analysis in family planning.

Future work could enhance the `ss2emu` package by making the data input process simpler, removing some of the complexity of the SS-to-EMU tool. Additionally, improving the Shiny web application with more interactive visualisations could enhance usability for non-technical users, allowing them to better explore and interpret outputs.

Overall, this thesis has made valuable contributions to the enhancement of family planning monitoring, particularly in the calculation and use of EMUs in FPET. By addressing uncertainties, improving utility, and developing `ss2emu`, this work strengthens our ability to track modern contraceptive use. These advancements are especially critical for low- and middle-income countries (LMICs), where reliable data is often sparse but essential for effective decision-making and monitoring family planning progress.

This work also represents a significant step forward in advancing the use of routinely collected administrative health data in LMICs. By leveraging and developing upon statistical methods that correct biases, quantify uncertainties, and enhance the reproducibility of estimates, we have made valuable contributions to the field. These innovations support more frequent, evidence-based decision-making, ensuring family planning programs are more responsive to the populations they aim to serve.

In conclusion, by improving the use of service statistics, a routinely collected administrative health data to generate reliable estimates of family planning indicators, this thesis directly contributes to the achievement of SDG Target 3.7, which aims to ensure universal access to sexual and reproductive health care (World Health Organization). The methods and tools developed here not only enhance the accuracy and accessibility of family planning data but also empower countries to track their progress toward reproductive health goals with confidence, ultimately helping to serve the needs of their populations more effectively.

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APPENDIX A

Appendix to Chapter 2

Estimating the Annual Number of Users Prior to Adjustment for Each Contraceptive Method

To estimate the number of modern contraceptive users in a given year, three groups of women are considered: short-term method (STM) users, recorded long-acting and permanent methods (LAPM) users, and historic LAPM users.

STM Users

For short-term methods, adjustments are made to focus on the number of users rather than the quantity of commodities distributed. This is achieved by standardising service statistics data using the couple-years protection factor (CYP), which reflects the duration of contraceptive protection provided by a given contraceptive unit or visit (U.S. Agency for International Development). For example, the CYP factor for injectables is 4, meaning that 4 units of injectables represent one protected user in a given year. Consequently, the commodity data for injectables is divided by 4 to account for this protection.

Let $\theta_{c,s,t,m}$ denote the number of users in country c, captured by service statistic type s, at time t, of method m. Let $x_{c,s,t,m}$ represent the observed quantities, and $q_{m,s}$ be the CYP adjustment factor for method m based on service statistics type

s. Where m is a STM, the number of users is given by:

$$\theta_{c,s,t,m} = x_{c,s,t,m} \cdot \frac{1}{q_{m,s}}. \tag{A.1}$$

LAPM Users and Historic LAPM Users

Long-acting and permanent methods (LAPMs) provide contraceptive protection for extended periods, spanning multiple years. Therefore, users of LAPMs should be recorded over the years they are protected. Historic LAPM users are those who began using the method before the first year of service statistics data collection, while continuing LAPM users are those recorded during the data collection period who continue to be tracked in subsequent years.

Total LAPM users are calculated as the sum of the new users of that method in a given year, the continuing LAPM users that should be accounted for in that year, and the historic LAPM users that should also be included. Historic and continuing LAPM users are calculated using method-specific continuation rates, allowing the continuity of a method to influence how many users from previous years carry through into the current year (Data For Impact [a]).

Where m is a LAPM, the total number of users in country c, captured by service statistics type s, at time t, for method m is calculated as:

$$\theta_{c,s,t,m} = u_{c,s,t,m} + h_{c,s,t,m}, \tag{A.2}$$

where $\theta_{c,s,t,m}$ represents the total number of LAPM users in country c for method m in year t and service statistics type s. The variable $u_{c,s,t,m}$ indicates the recorded number of users (observed and continuing) in country c for method m in year t and service statistics type s. The term $h_{c,s,t,m}$ denotes the historic number of users in country c for method m in year t and service statistics type s.

The formula for recorded number of users is given by:

$$u_{c,s,t,m} = \sum_{k=0}^{t-t_0} \left(x_{c,m,t-k,s} \cdot \alpha_{m,k+1} \right), \tag{A.3}$$

where $u_{c,s,t,m}$ represents the total number of recorded users for country c, method m, year t, and data type s. The variable $x_{c,s,t,m}$ refers to the recorded users for country c, method m, year t, and data type s. The continuation rate for method m after k years of use is denoted by $\alpha_{m,k}$. Finally, t_0 signifies the first year of data collection.

The number of historic users is calculated as:

$$h_{c,s,t,m} = \sum_{k=t-t_0}^{16} (x_{c,m,t_0,s} \cdot \alpha_{m,k}) \cdot \gamma_{c,m}, \tag{A.4}$$

where $h_{c,s,t,m}$ represents the historic number of users in country c for method m in year t and service statistics type s, $x_{c,m,t_0,s}$ refers to the number of observed users in country c for method m for the first year of recorded data, and $\gamma_{c,m}$ is the scaling factor specific to country c for method m, defined as:

$$\gamma_{c,m} = \begin{cases} 1 & \text{if method } m \text{ in country } c \text{ was consistently available in the past,} \\ 0.5 & \text{if method } m \text{ in country } c \text{ was scaling up in use,} \\ 0 & \text{if method } m \text{ in country } c \text{ was newly introduced in year } t_0. \end{cases} \tag{A.5}$$

Supplementary Figures

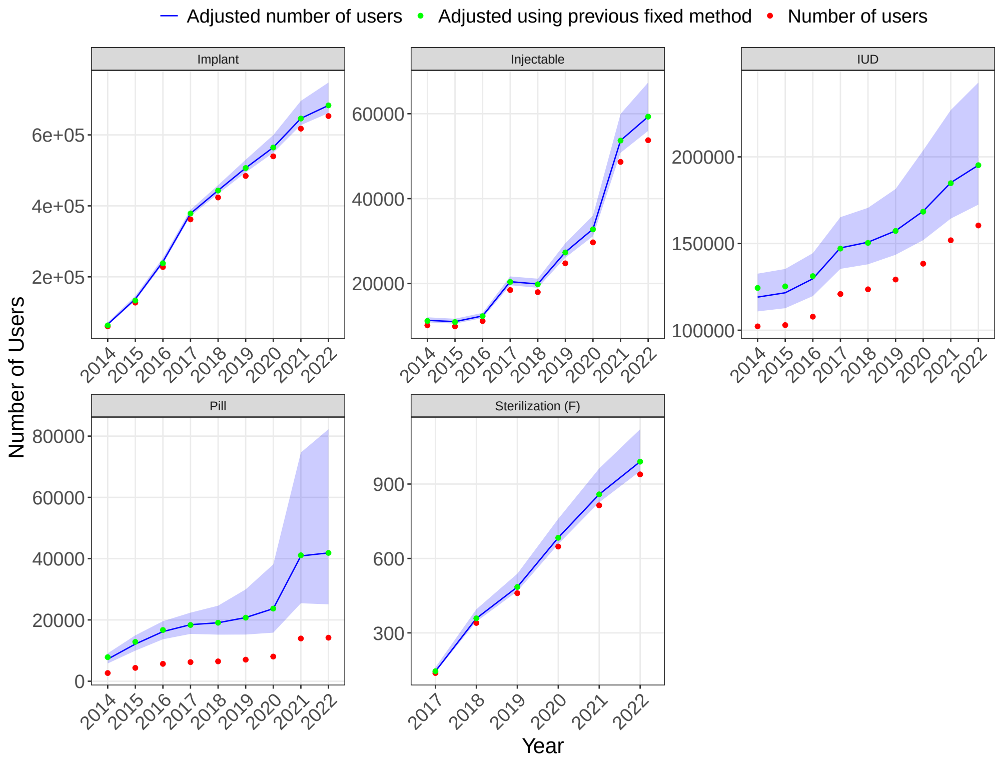


Figure A.1: This plot illustrates the annual number of users by contraceptive method captured in family planning visits data in Country 1. The red points reflect user counts before the private sector adjustment. The green points represent the adjusted user counts using the previous fixed private sector adjustment. The solid line represents the median estimate of adjusted users following the updated private sector adjustment, while the shaded area indicates the 95% credible interval associated with these estimates.

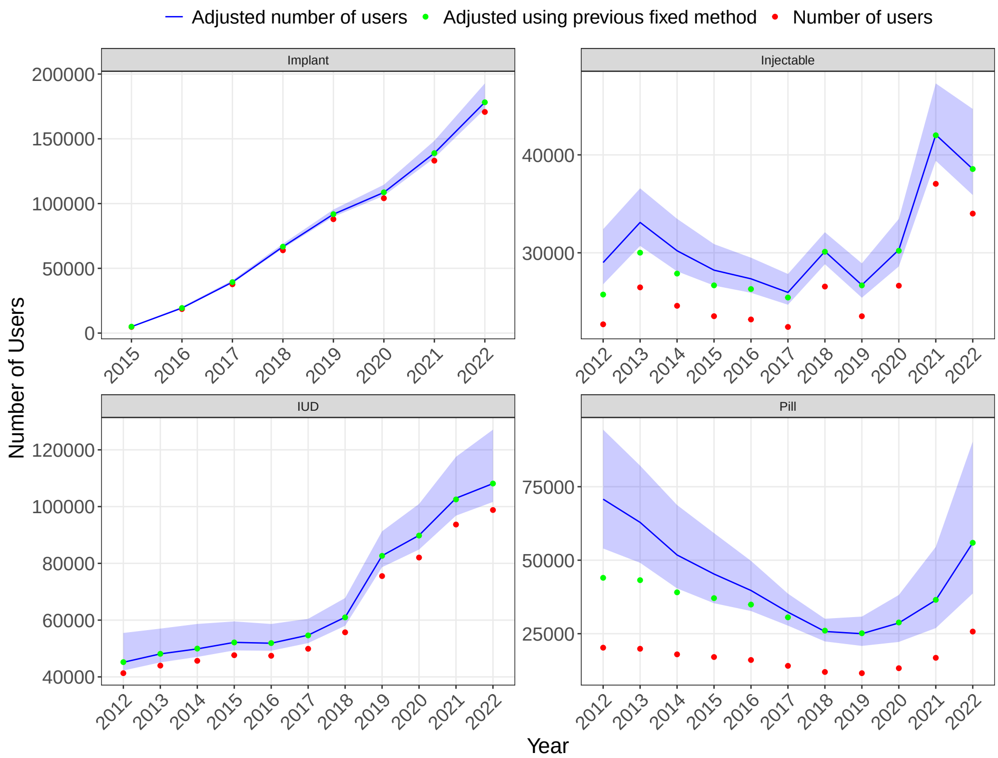


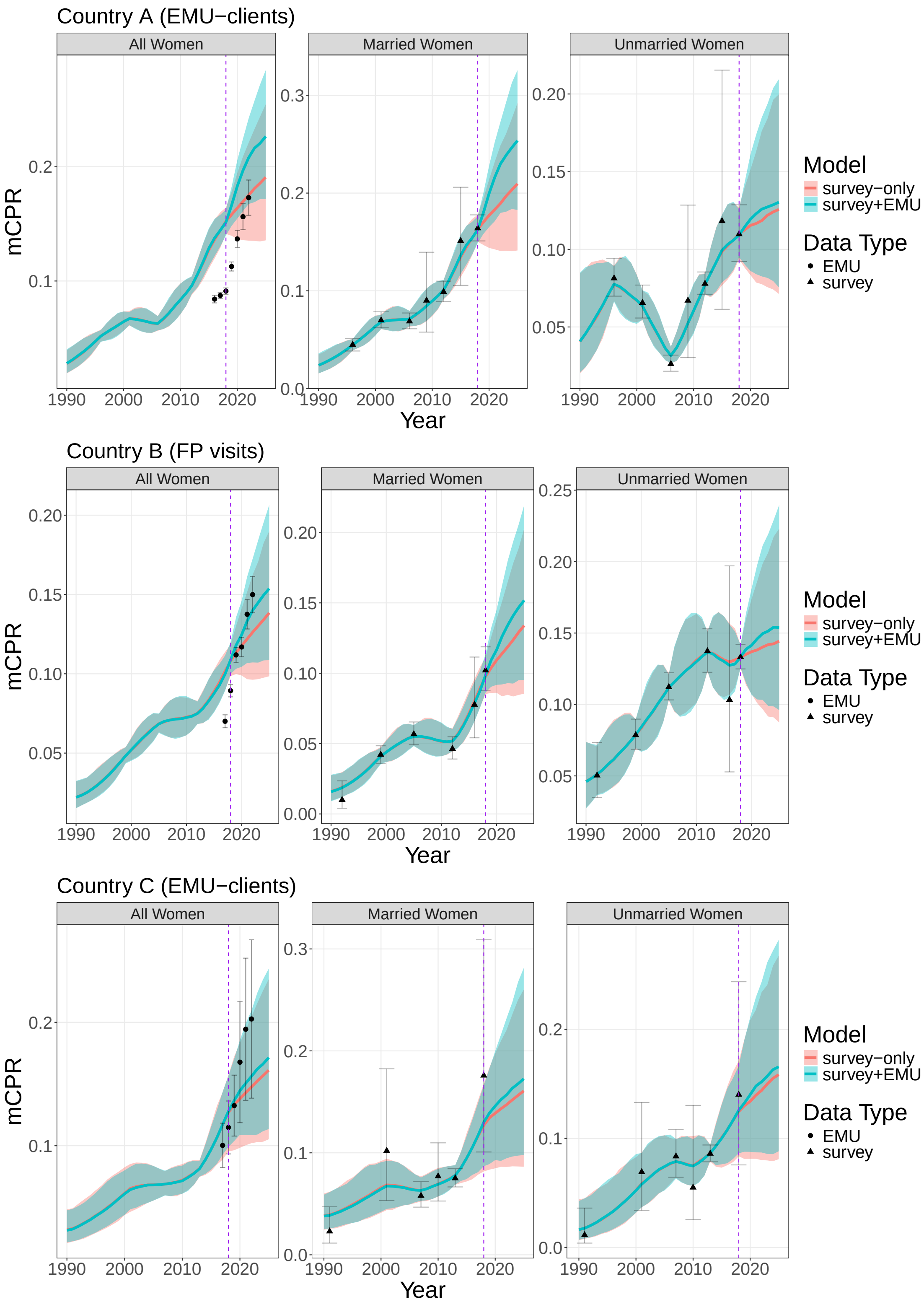
Figure A.2: This plot illustrates the annual number of users by contraceptive method captured in family planning visits data in Country 2. The red points reflect user counts before the private sector adjustment. The green points represent the adjusted user counts using the previous fixed private sector adjustment. The solid line represents the median estimate of adjusted users following the updated private sector adjustment, while the shaded area indicates the 95% credible interval associated with these estimates.

APPENDIX B

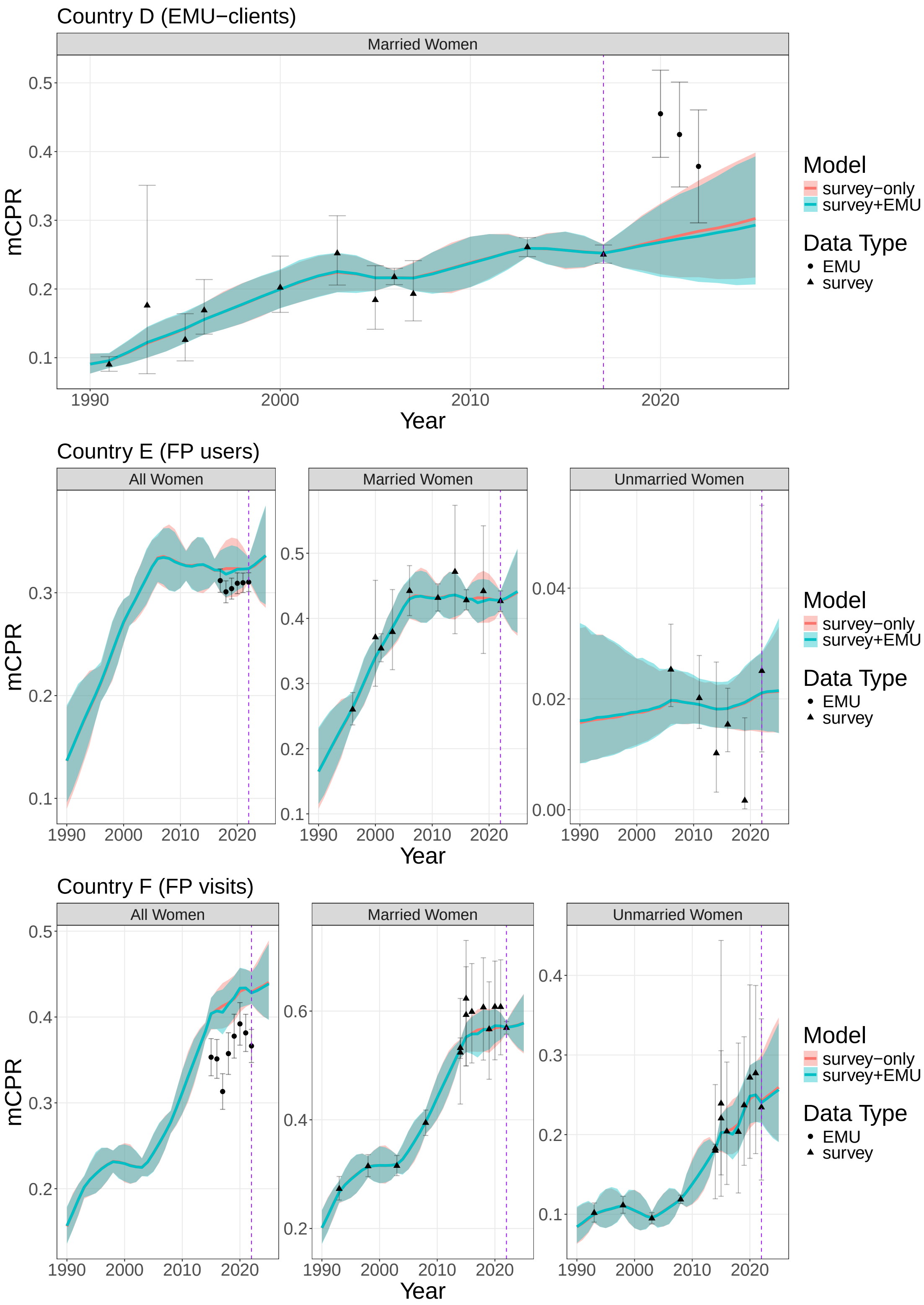
Appendix to Chapter 3

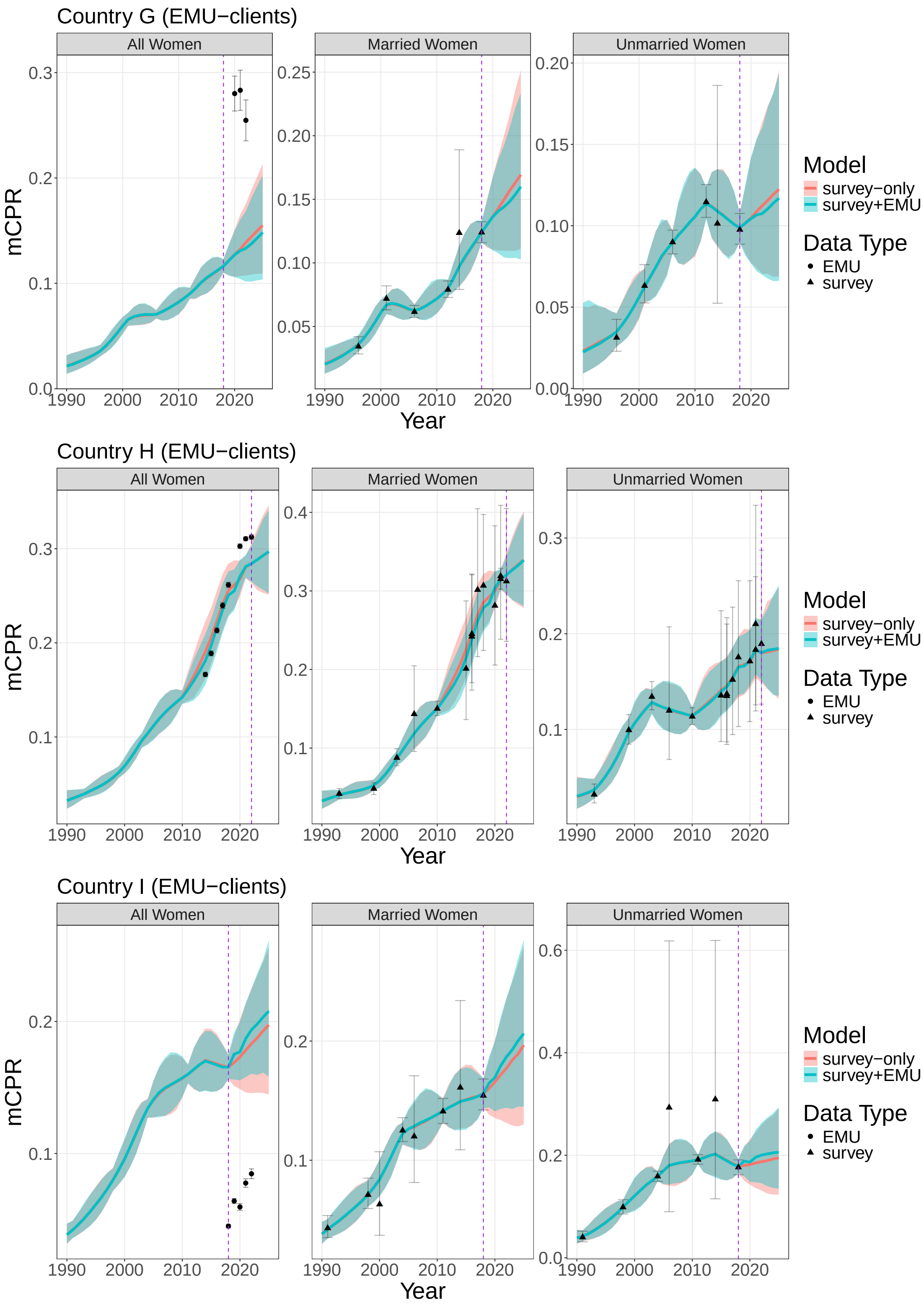
Results for all countries

Estimates of mCPR for MWRA, UWRA, and WRA for all countries in the 2023 EMU database. Solid lines indicate median estimates of mCPR, shaded regions show the 95% credible intervals. Results in red highlight the use of the survey-only model. Results in blue highlight the use of surveys and EMU. The error bars represent the 95% confidence interval associated with the data. The purple dashed line marks the year of the most recent survey.

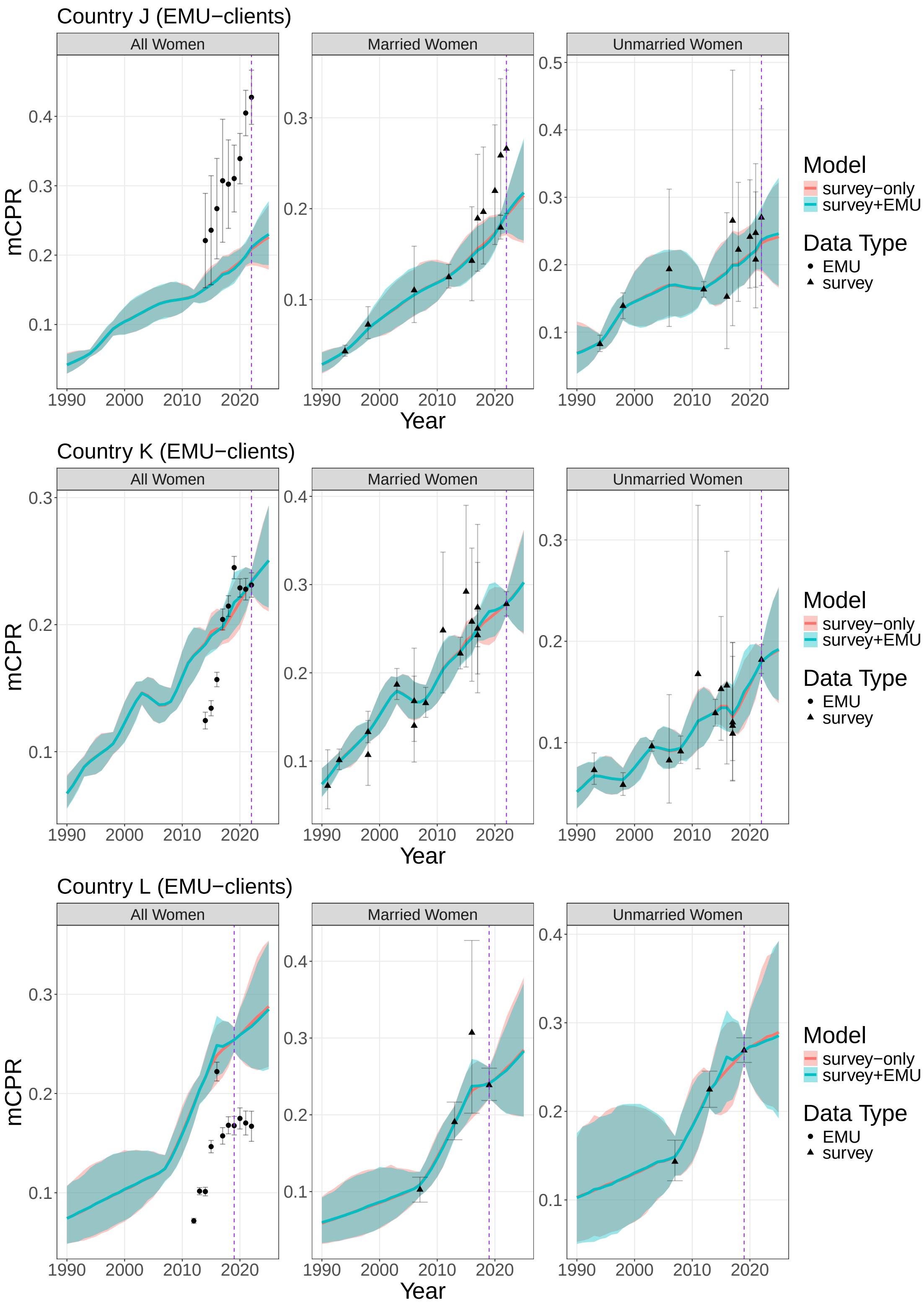


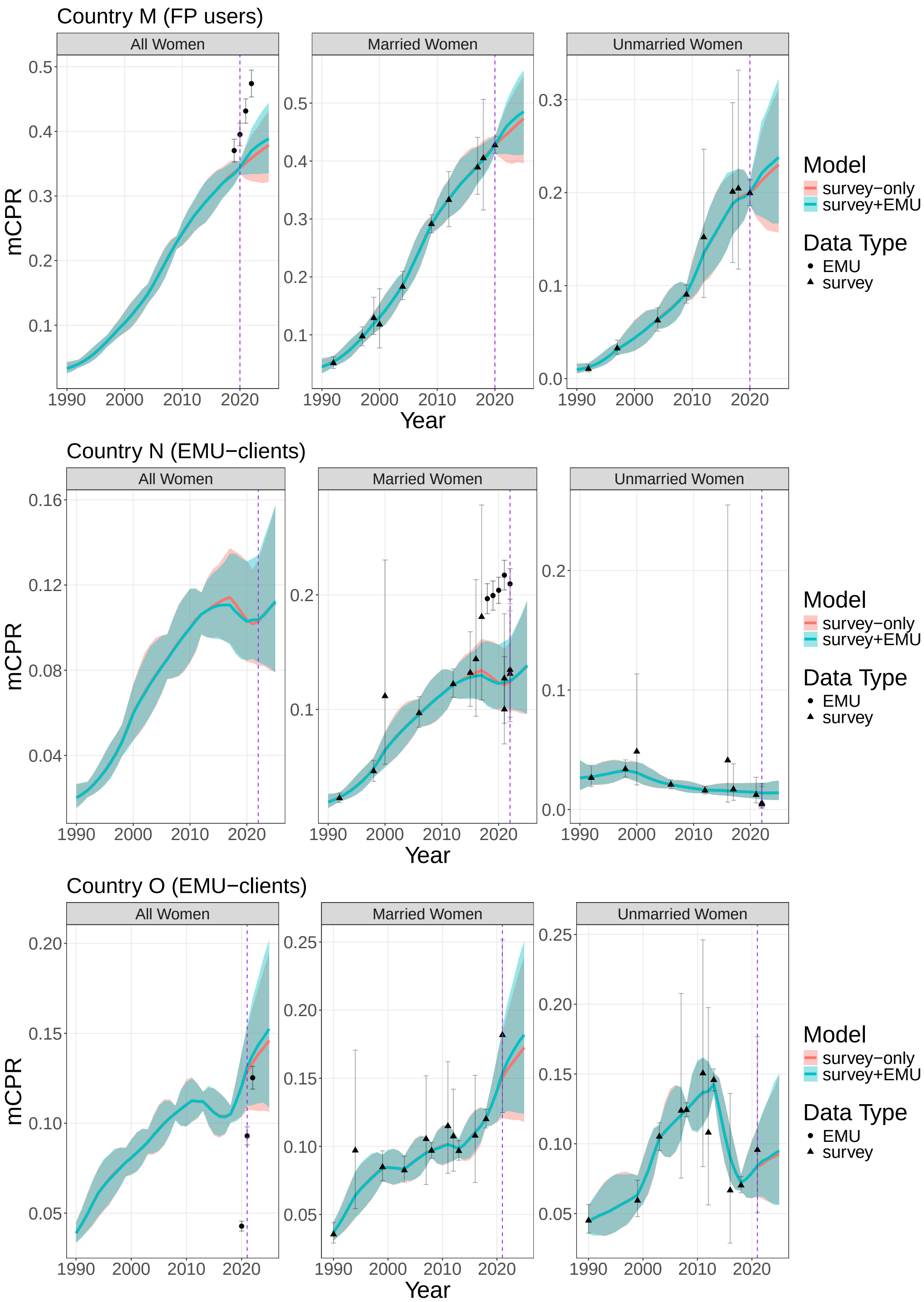
Country A (EMU−clients)
All Women
Married Women
Unmarried Women
mCPR
Year
Country B (FP visits)
All Women
Married Women
Unmarried Women
mCPR
Year
Country C (EMU−clients)
All Women
Married Women
Unmarried Women
mCPR
Year
Model
survey−only
survey+EMU
Data Type
EMU
survey


Country D (EMU−clients)
Married Women
mCPR
Year
Model
survey−only
survey+EMU
Data Type
EMU
survey
Country E (FP users)
All Women
Married Women
Unmarried Women
mCPR
Year
Model
survey−only
survey+EMU
Data Type
EMU
survey
Country F (FP visits)
All Women
Married Women
Unmarried Women
mCPR
Year
Model
survey−only
survey+EMU
Data Type
EMU
survey

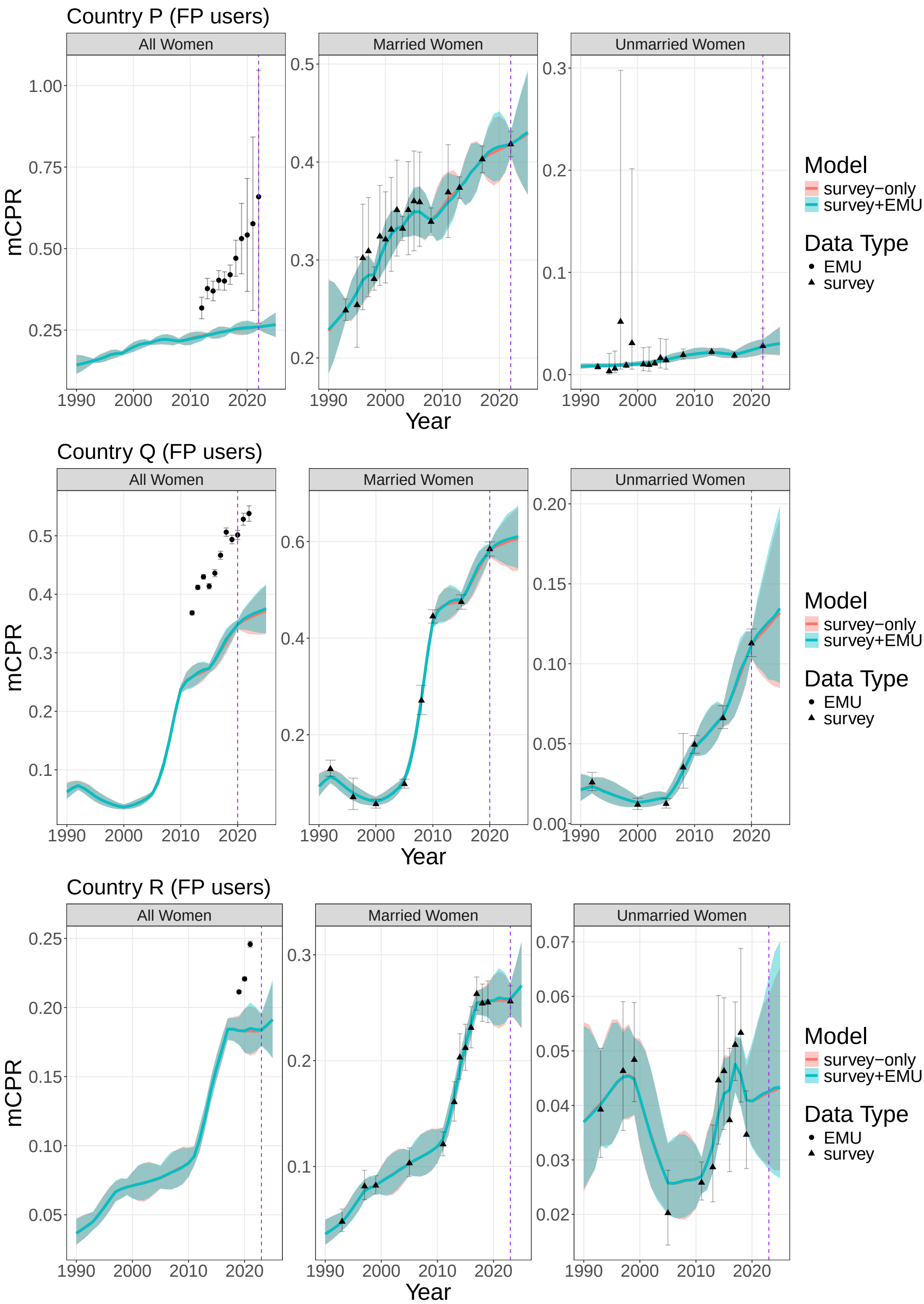


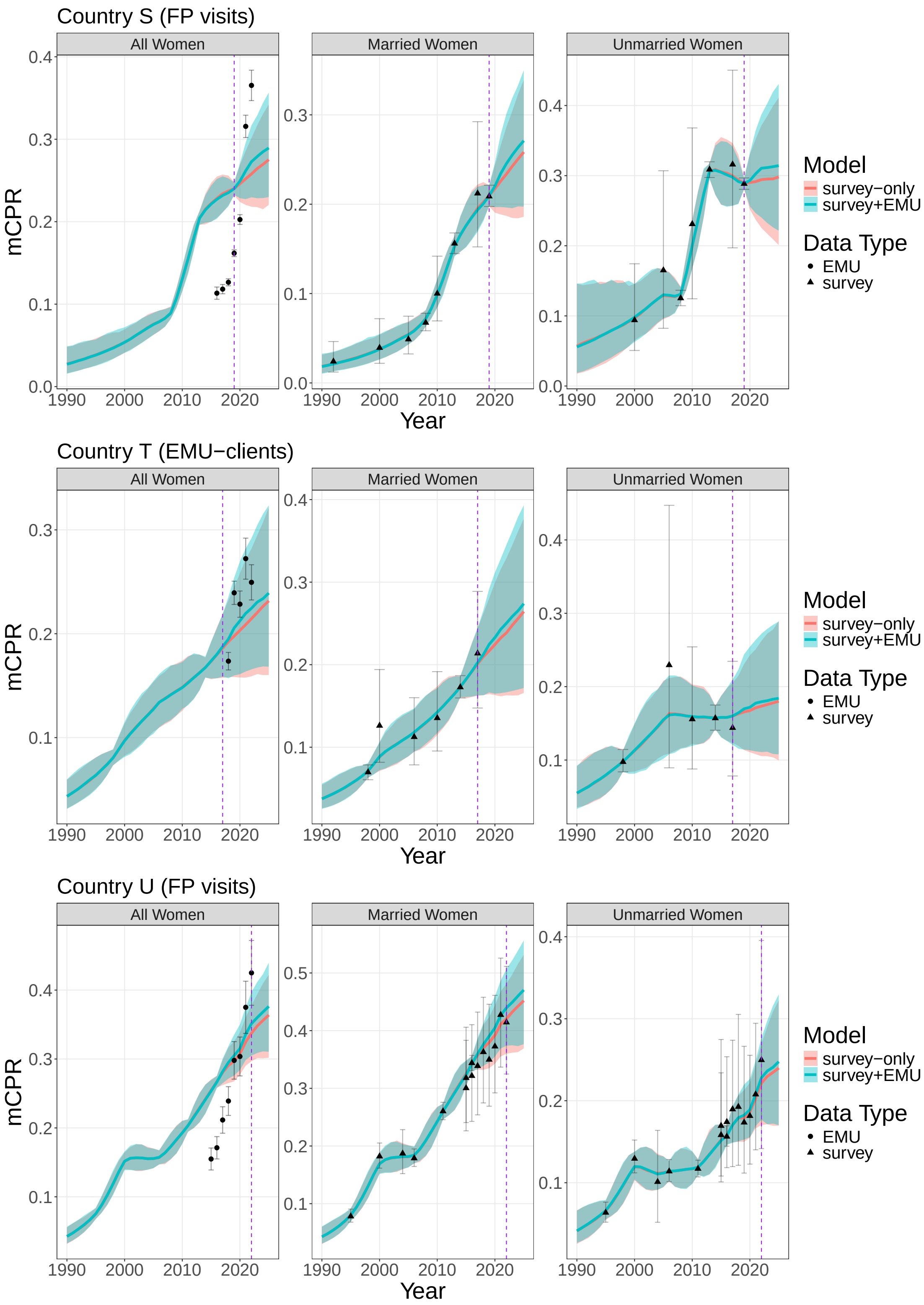
Country G (EMU−clients)
All Women
Married Women
Unmarried Women
mCPR
Year
Model
survey−only
survey+EMU
Data Type
EMU
survey
Country H (EMU−clients)
All Women
Married Women
Unmarried Women
mCPR
Year
Model
survey−only
survey+EMU
Data Type
EMU
survey
Country I (EMU−clients)
All Women
Married Women
Unmarried Women
mCPR
Year
Model
survey−only
survey+EMU
Data Type
EMU
survey

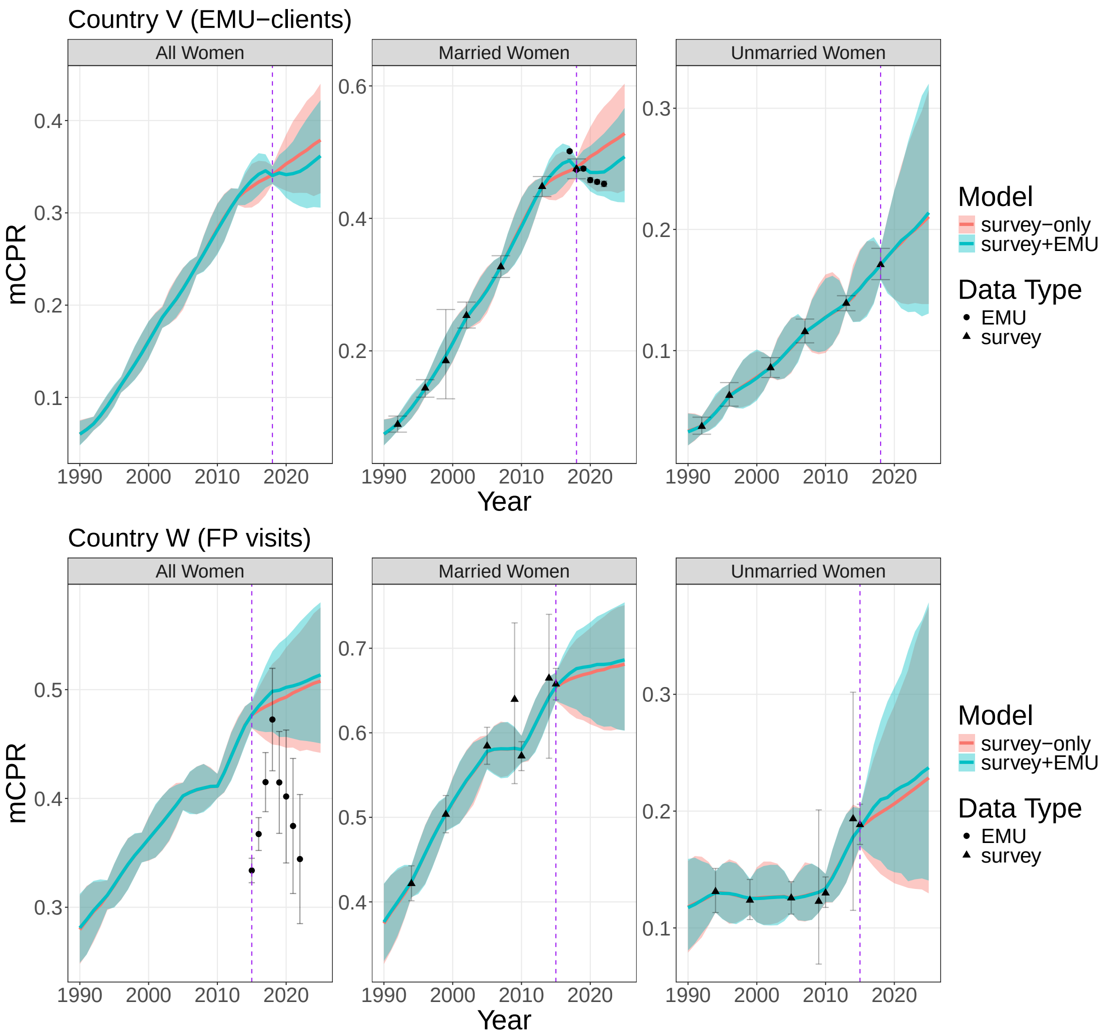

Country J (EMU−clients)
All Women
Married Women
Unmarried Women
mCPR
Year
Country K (EMU−clients)
All Women
Married Women
Unmarried Women
mCPR
Year
Country L (EMU−clients)
All Women
Married Women
Unmarried Women
mCPR
Year
1990 2000 2010 2020
Model
survey−only
survey+EMU
Data Type
EMU
survey



Country M (FP users)
All Women
Married Women
Unmarried Women
mCPR
Year
Model
survey−only
survey+EMU
Data Type
EMU
survey
Country N (EMU−clients)
All Women
Married Women
Unmarried Women
mCPR
Year
Model
survey−only
survey+EMU
Data Type
EMU
survey
Country O (EMU−clients)
All Women
Married Women
Unmarried Women
mCPR
Year
Model
survey−only
survey+EMU
Data Type
EMU
survey


Country P (FP users)
All Women
Married Women
Unmarried Women
mCPR
Year
Country Q (FP users)
Country R (FP users)
Model
survey−only
survey+EMU
Data Type
EMU
survey
1990
2000
2010
2020


Country S (FP visits)
All Women
Married Women
Unmarried Women
mCPR
Year
Model
survey−only
survey+EMU
Data Type
EMU
survey
Country T (EMU−clients)
All Women
Married Women
Unmarried Women
mCPR
Year
Model
survey−only
survey+EMU
Data Type
EMU
survey
Country U (FP visits)
All Women
Married Women
Unmarried Women
mCPR
Year
Model
survey−only
survey+EMU
Data Type
EMU
survey


Country V (EMU−clients)
All Women
Married Women
Unmarried Women
mCPR
Year
Model
survey−only
survey+EMU
Data Type
EMU
survey
Country W (FP visits)
All Women
Married Women
Unmarried Women
mCPR
Year
Model
survey−only
survey+EMU
Data Type
EMU
survey