Online Appendix 1

Estimation of annual numbers of patients starting ART and calibration to HIV testing data

Overview: Estimation of annual numbers of patients starting ART

The estimation of the annual number of patients starting ART in each province follows a three-step process. In the first step, we obtain rough initial estimates based on manual calibration of a simplified model to the reported ART totals in each province. In the second step, we follow a more formal Bayesian approach to fitting the Thembisa model to the reported ART totals in each province, setting the priors based on the initial rough estimates. In the final step, we follow a procedure similar to that in the second step, but applied specifically to the paediatric ART estimates. Each of these steps is described in more detail in the sections that follow.

In the sections that follow, we will use the symbol $S_d^i(t,p)$ to represent the estimated number of patients starting ART in year *t*, in demographic group *d* (0 = adult males, 1 = adult females and 2 = children < 15 years), at step *i* in the estimation process (so that $S_d^1(t,p)$ represents the initial estimates obtained in the manual calibration step), in province *p*. When the set of all $S_d^i(t,p)$ values for a particular province are entered into the Thembisa model, the model will yield estimates of $M_c(t,p)$, the number of patients cumulatively enrolled up to time *t*, in group *c* (*c* is 1 if the total relates only to children and is 0 otherwise) and $N_c(t,p)$, the number of patients currently receiving ART at time *t*, in group *c*.

Data sources: ART patient numbers

There are two types of data used in the calibration: reported numbers of patients receiving ART in the public sector and reported numbers of patients receiving ART in either the private sector or NGO programmes operating outside of the public sector. Private sector statistics date from 2001, whereas public sector statistics date from the start of the public sector programme in 2004. The public sector totals are obtained from various published and unpublished government reports.[1] The reporting of public sector totals has not been consistent over time, with many provinces switching from reporting of cumulative ART enrolment to current ART enrolment in 2009. In addition, reporting practices are not consistent between provinces, and even within provinces there may be inconsistencies, with some clinics reporting cumulative enrolment and others reporting current enrolment.

The private and NGO totals are estimated through biennial surveys of major disease management programmes and NGOs, which yield estimates of the numbers of patients currently on ART at the middle of each survey year.[2,3,4] The method for estimating the number of individuals treated in the private and NGO sector has been published previously.[2] In the two most recent surveys (mid-2012 and mid-2014), it proved difficult to obtain information on the numbers of individuals treated through NGO programmes. However, it is believed that the numbers of patients on ART in NGO programmes have been gradually declining, as PEPFAR-funded NGO programmes have been integrated into the public sector programme. PEPFAR funding is expected to reduce substantially by 2017,[5] and we have therefore approximated the numbers receiving ART through NGO programmes (not included in the public sector ART statistics) by assuming a linear decline to zero over the period from mid-2011 to mid-2017. Although this is crude, the contribution of NGO programmes to total ART provision has become increasingly small over the last decade, accounting for less than 5% of ART provision in 2010.[4] The approximation is therefore not likely to substantially affect the estimated overall levels of ART provision.

The totals for the private sector and the NGO sector were then split between provinces. Because of lack of recent data on the provincial profile of ART provision in the private and NGO sectors, we relied on the same provincial ART distributions as assumed in an earlier modelling study.[3] In the case of the private sector, these assumptions were derived from the provincial distribution of patients treated through the Aid for AIDS programme,[6] which treated the majority of private sector ART patients for most of the last decade. In the case of the NGO sector, the assumed provincial distribution was based on information provided by NGO programmes at the time of the 2008 survey.

In the sections that follow, we use the symbol $R_c^s(t,p)$ to represent the reported level of ART enrolment at time *t*, in group *c*, in sector *s* (0 for public, 1 for private/NGO), and in province *p*. Because the private/NGO numbers are small relative to the public sector numbers, it is the latter that we are most interested in when calibrating the model. The private sector totals are therefore included in the calibration only at the mid-year time points prior to the start of the public sector ART rollout in 2004, and at the time points for which public sector statistics are reported in subsequent periods (for time points at which a public sector total is reported but there is no corresponding reported private sector total, the private sector total is approximated by linearly interpolating between the nearest reported private sector totals). We use the symbol $n_c(p)$ to represent the number of time points for which we have reported ART enrolment statistics for the public sector (or private sector pre-2004), and we use the symbol $T_c(p)$ to represent the set of these time points.

The symbol τ_p represents the time up to which all reported public sector totals in province *p* are known to represent cumulative ART enrolment (in most provinces this will be some time in 2009). After time τ_p, there is uncertainty as to whether the reported public sector totals represent cumulative enrolment, current enrolment or some combination of the two. (This uncertainty is addressed in the uncertainty analysis described in Step 2 below.)

Step 1: Initial estimation based on manual calibration

Our approach to setting the assumed numbers of public sector patients starting ART in each year is to create a simplified

model that projects both cumulative enrolment and current ART numbers over time, and to calibrate this model to reported public sector statistics for each province. The simplified model updates the numbers of patients on ART at monthly time steps, stratifying the treated population by time since ART initiation (in months) and allowing for ART mortality and treatment interruptions, as well as changes because of migration.

A similar process is followed in estimating the annual numbers of children starting ART in each province through the public sector programme, with the same model being calibrated to the reported numbers of children on ART. (The only difference to the model is that it allows for children to age out of the treated paediatric population when they reach age 15 years.) The model estimate of the number of adults starting ART in the public sector is then calculated as the difference between the total number enrolled, as estimated in the previous step, and the estimated number of children enrolled. The split between adult males and adult females is assumed to change over time, based on data from the TIER reporting system.[7] The split between men and women in the public sector is also assumed to differ between provinces, based on public sector statistics in 2012.[1]

Following a similar procedure, the number of private and NGO patients starting ART in each year was then estimated for each province using the same simplified model. The assumed numbers of new initiates were set in such a way as to ensure that the modelled numbers on ART matched the estimated totals in each province. The numbers of new ART initiates in the private and NGO sector were then divided among the child, adult male and adult female categories using the proportions 6.8%, 41.1% and 52.1%, respectively, based on data submitted by medical schemes to the Risk Equalisation Fund up to 2008.

Finally, the estimates for the private and public sectors were added to obtain the total number of ART patients starting ART in each demographic group and in each year.

Step 2: Bayesian uncertainty analysis

To ensure a smooth progression in ART enrolment over time, we apply a smoothing technique called Bayesian B-splines in calibrating the model to the reported ART totals.[8] This method has previously been used in the calibration of HIV models to HIV prevalence data[9] and is based on a series of overlapping polynomial splines, which when added together with different weights yield a smooth time series. The Bayesian approach has the advantage of yielding posterior distributions to represent the uncertainty around the estimated ART enrolment statistics.

Because the model inputs are annual numbers of patients starting ART, we only require the splines to yield estimates at integer intervals. We have therefore chosen fairly simple splines, each defined over an interval of four years, with maximum value (1) at the mid-point of the interval, values of 0.5 at times 1 and 3 after the start of the interval, and values of 0 at the start and end of the interval. The spline knots are at 2-year intervals, with the first spline having its maximum value in 2000, the second spline having its maximum value in 2002 and so on up to 2014. The splines are fitted on the natural log scale, to avoid negative numbers of patients starting ART and to help normalise the variance of the model error terms. The symbol $B_j^c(p)$ represents the *j*th B-spline coefficient in province *p* (for the purpose of Step 2, we are considering adults and children combined, so *c* = 0). The first B-spline coefficient, $B_1^0(p)$, is therefore comparable to

$$\ln\left(S_0^i(2000,p)+S_1^i(2000,p)+S_2^i(2000,p)\right), \quad \text{[Eqn 1]}$$

whereas the second B-spline coefficient, $B_2^0(p)$, is comparable to

$$\ln\left(S_0^i(2002,p)+S_1^i(2002,p)+S_2^i(2002,p)\right). \quad \text{[Eqn 2]}$$

For the odd years, we interpolate between the coefficients for the nearest even years, to ensure a smooth progression in ART enrolment numbers. For example, $0.5\times\left(B_1^0(p)+B_2^0(p)\right)$ yields the model estimate of the total number of patients starting ART in province *p* in 2001 (on the natural log scale).

We initially estimate B-spline coefficients for each province by applying standard linear regression models to the log-transformed $S_d^1(t,p)$ estimates from Step 1 (i.e. regressing the $B_j^0(p)$ values on the log-transformed $S_d^1(t,p)$ values). These form the basis for the prior distributions (discussed below). The same prior distributions are assumed for all provinces. This means that even though the prior distributions for a particular province are to some extent dependent on the ART data from that province, the reliance on the ART data from that province is diminished because we are effectively averaging across all provinces when we set the prior distributions.

Prior distributions

The first prior distribution represents the uncertainty regarding the $B_1^0(p)$ parameter (the total number of patients starting ART in 2000–2001, on the natural log scale). The estimates from the linear regressions referred to in the previous paragraph range from 4.28 to 7.81. A normal prior distribution is assumed, with the same mean and standard deviation as estimated from the nine provinces (6.27 and 1.06, respectively). The 2.5 and 97.5 percentiles of this distribution are 4.20 and 8.35, respectively, and the prior distribution is thus wide enough to include all of the coefficients estimated from the $S_d^1(t,p)$ values.

The second prior distribution represents the uncertainty regarding the variable $u_2^0(p)\equiv B_2^0(p)-B_1^0(p)$ (the difference

between the total number starting ART in 2002–2003 and 2000–2001, on the natural log scale). A normal prior distribution is assumed, with the same mean and standard deviation as estimated when the quantity $u_2^0(p)$ is estimated for each of the nine provinces (0.45 and 0.19, respectively). This means that the 2.5 and 97.5 percentiles for the quantity $B_2^0(p) - B_1^0(p)$ are 0.08 and 0.82, respectively.

For values of $j > 2$, the B-spline coefficients $B_j^0(p)$ are modelled by assuming the coefficients follow a second-order random walk[8,9]:

$$B_j^0(p) = 2B_{j-1}^0(p) - B_{j-2}^0(p) + u_j^0(p), \quad \text{[Eqn 3]}$$

with Gaussian errors $u_j^0(p) \sim N(\mu_j, \sigma_j^2)$. We, therefore, assign a normal prior distribution to each of the $u_j^0(p)$ terms (in total there are six such terms for each province, for the B-splines corresponding to total new enrolment in 2004–2005, 2006–2007, …, 2014–2015). For $j = 3$, μ_j and σ_j^2 are set at 1.39 and 0.51, respectively, reflecting the steep increase in rates of ART enrolment when the public sector began in 2004 (as for $u_2^0(p)$), these parameters are calculated from the regression coefficients estimated for the different provinces in the first estimation step). For $j = 4$, μ_j and σ_j^2 are set at -0.76 and 0.94, respectively, implying a slowdown in the growth of ART rollout in 2006. For $j > 4$, the changes in coefficients appear to be more stable, so μ_j and σ_j^2 are set at -0.35 and 0.47, respectively, for all $j > 4$. The approach adopted here differs from that in other Bayesian B-spline applications,[8,9] where a hyperprior is assigned to represent the uncertainty regarding the σ_j^2 parameter, but the same σ_j^2 value is assumed for all j, and μ_j is set to zero.

Finally, a prior distribution is specified to represent the uncertainty regarding the transition from reporting cumulative ART enrolment to reporting current ART enrolment in the public sector. We define ϑ_p to be the annual change in the fraction of public ART services that report current enrolment, after time τ_p. In other words, if *f(t, p)* is the fraction of public ART services that report cumulative enrolment at time *t*, then

$$f(t,p) = \begin{cases} 1 & \text{if } t < \tau_p \\ \exp\left(-\theta_p\left(t - \tau_p\right)\right) & \text{if } t \geq \tau_p \end{cases} \quad \text{[Eqn 4]}$$

The quantity $\exp(-\vartheta_p)$ must be between 0 and 1. Because we have no prior knowledge regarding the pace of change in the reporting, we assign a vague prior (uniform on the interval [0, 1]) to represent the uncertainty regarding $\exp(-\vartheta_p)$. The τ_p parameter is set to the start of August 2009 for all provinces except North West (for which it is set to the start of June 2011) and Western Cape (which has always reported numbers currently on ART – The τ_p parameter is therefore omitted from the uncertainty analysis for this province).

We define $\boldsymbol{\Theta}_p$ to be the vector of parameters that are being considered in the Bayesian uncertainty analysis, that is, $\boldsymbol{\Theta}_p = \left\{B_1^0(p), u_2^0(p), u_3^0(p), \ldots, u_8^0(p), \theta_p\right\}$. For a given parameter combination, it is possible to calculate the $S_d^2(t,p)$ parameters that we are attempting to estimate. Firstly, define $S^2(t,p)$ to be the Step 2 estimate of the total number of patients starting ART in year *t* in province *p*. Then

$$S^2(2000,p) = \exp\left(B_1^0(p)\right)$$

$$S^2(2001,p) = \exp\left(B_1^0(p) + 0.5u_2^0(p)\right)$$

$$S^2(2002,p) = \exp\left(B_1^0(p) + u_2^0(p)\right)$$

$$S^2(2003,p) = \exp\left(B_1^0(p) + u_2^0(p) + 0.5u_3^0(p)\right)$$

…

$$S^2(2014,p) = \exp\left(B_1^0(p) + \sum_{j=2}^{8} u_j^0(p)\right) \quad \text{[Eqn 5]}$$

For the sake of simplicity, we set the paediatric numbers at the same level as in the first step, but rescale the adult male and adult female numbers so that the fraction of adult ART initiators who are male remains the same as in the first step. Thus for children,

$$S_2^2(t,p) = S_2^1(t,p). \quad \text{[Eqn 6]}$$

For adult males,

$$S_0^2(t,p) = \left(S^2(t,p) - S_2^1(t,p)\right)\frac{S_0^1(t,p)}{S_0^1(t,p) + S_1^1(t,p)}, \quad \text{[Eqn 7]}$$

and for adult females,

$$S_1^2(t,p) = \left(S^2(t,p) - S_2^1(t,p)\right)\frac{S_1^1(t,p)}{S_0^1(t,p) + S_1^1(t,p)}. \quad \text{[Eqn 8]}$$

With these equations, $S_0^2(t,p) + S_1^2(t,p) + S_2^2(t,p) = S^2(t,p)$. The paediatric totals are updated in Step 3, described below.

Likelihood function

The likelihood function represents how well the model fits the reported numbers of patients on ART. For the purpose of calculating the likelihood, we assume that the error terms (the differences between the modelled number of patients on ART and the corresponding reported numbers of ART patients, on a log scale) are normally distributed with zero mean and variance σ_m^2.

Firstly, we define the reported total to be the sum of the totals reported for the private and public sectors:

$$\Omega(t,p) = R_0^0(t,p) + R_0^1(t,p). \quad \text{[Eqn 9]}$$

Secondly, we define $G(\boldsymbol{\Theta}_p,t)$ to be the model estimate of the number of patients we would expect to be reported as on ART at time t, if parameter combination $\boldsymbol{\Theta}_p$ represented the 'true' set of model parameters. This estimate depends on the assumed fraction of ART services that report cumulative enrolment, which in turn depends on the fraction of patients receiving ART through the public sector (because only the public sector facilities report cumulative enrolment). The Thembisa model does not directly simulate the fraction of patients receiving ART through the public sector, so we approximate this fraction by the quantity

$$\phi(t,p) = 1 - R_0^1(t,p) \big/ N_0(t,p). \quad \text{[Eqn 10]}$$

If $f(t,p)>0$, then we calculate $G(\boldsymbol{\Theta}_p,t)$ as

$$G(\Theta_p,t) = R_0^1(t,p) + f(t,p)\, M_0(t,p)\phi(t,p) + \left(1 - f(t,p)\right) N_0(t,p)\phi(t,p). \quad \text{[Eqn 11]}$$

This simplifies to $G(\boldsymbol{\Theta}_p,t)=N_0(t,p)$ if $f(t,p)=0$. If $f(t,p)\leq 0$, this implies that all ART is provided through the private sector, which reports current ART enrolment. Thus we use the same simplified formula, $G(\boldsymbol{\Theta}_p,t)=N_0(t,p)$, if $f(t,p)\leq 0$.

The variance of the error terms is approximated by the formula:

$$\hat{\sigma}_m^2 = \frac{1}{n_0(p)} \sum_{t \in T_0(p)} \left(\ln\left(G(\Theta_p,t)\right) - \ln\left(\Omega(t,p)\right) \right)^2. \quad \text{[Eqn 12]}$$

The likelihood function is then calculated as

$$L(\Omega_p \mid \Theta_p) = \prod_{t \in T_0(p)} \frac{1}{\sqrt{2\pi}\hat{\sigma}_m} \exp\left(- \frac{\left(\ln\left(G(\Theta_p,t)\right) - \ln\left(\Omega(t,p)\right) \right)^2}{2\hat{\sigma}_m^2} \right), \quad \text{[Eqn 13]}$$

where Ω_p represents the vector of $\Omega(t,p)$ values, for all $t \in T_0(p)$.

Posterior simulation

The posterior distribution (which is proportional to the product of the prior and likelihood functions) is approximated using Incremental Mixture Importance Sampling (IMIS).[10] In the first IMIS step, a sample of 10 000 parameter combinations is randomly drawn from the prior distributions, and for each of these parameter combinations, we run the model to calculate the $G(\boldsymbol{\Theta}_p,t)$ values. In the second IMIS step, we define a second distribution based on the parameter combinations that yielded the best fit to the ART programme data in the previous step, and draw a second sample of 1000 parameter combinations from this second distribution. The procedure continues until there is a sufficiently diverse set of parameter combinations that yield similarly good fits to the ART data.

Results from Step 2

Table 1 shows the posterior mean estimates for each of the model parameters, compared with the prior means. As might be expected, the posterior means for the $B_1^0(p)$ parameter are smallest for the province with the smallest population (Northern Cape) and largest for the two provinces with the largest populations (Gauteng and KwaZulu-Natal). In four provinces (Eastern Cape, Free State, Gauteng and Northern Cape), there was a relatively rapid transition from reporting of cumulative enrolment to reporting of current enrolment, as shown by the low posterior means estimated for the $\exp(-\vartheta_p)$ parameter.

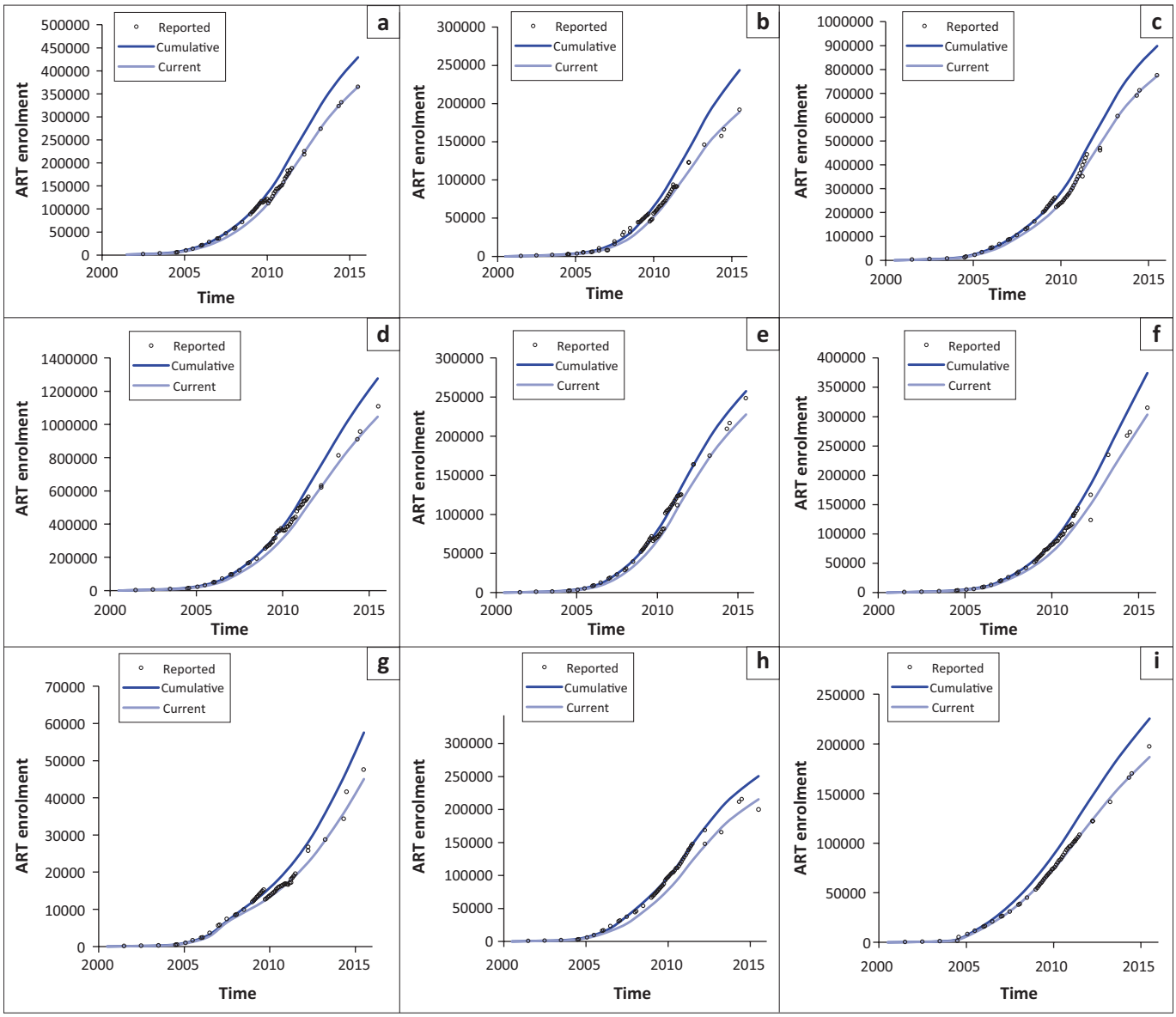
Figure 1 shows the results of this model calibration. In some provinces (Eastern Cape, Free State, Gauteng and Northern Cape), it is clear that there was a fairly abrupt change in the reporting (from cumulative totals to current totals) in late 2009. However, in a few cases (notably Limpopo and Mpumalanga), the change in reporting has been more gradual. In the case of North West province, it is known that the transition from reporting cumulative totals to reporting current totals occurred later than the other provinces, whereas in the Western Cape it is assumed that all totals reflect current enrolment.

Figure 2 shows the confidence intervals around the model estimates of current ART enrolment. The 95% confidence intervals around the posterior means are quite wide for some provinces (notably Free State and Western Cape).

TABLE 1: Prior and posterior means for Step 2 (adults and children combined).

Parameter	$B_1^0(p)$	$u_2^0(p)$	$u_3^0(p)$	$u_4^0(p)$	$u_5^0(p)$	$u_6^0(p)$	$u_7^0(p)$	$u_8^0(p)$	$\exp(-\theta_p)$
Prior mean	6.27	0.45	1.39	-0.76	-0.35	-0.35	-0.35	-0.35	0.50
Posterior mean									
EC	6.88	0.27	1.56	-0.88	-0.40	-0.02	-0.56	-0.38	0.10
FS	6.16	0.36	0.76	0.27	-0.43	-0.50	-0.36	-0.48	0.26
GT	7.58	0.41	1.51	-1.11	-0.35	0.17	-0.70	-0.53	0.01
KZ	7.88	0.27	1.33	-0.33	-0.69	-0.11	-0.47	-0.22	0.57
LM	6.02	0.34	1.28	-0.19	-0.79	-0.12	-0.69	-0.28	0.86
MP	6.48	0.31	0.90	0.27	-0.83	-0.07	-0.29	-0.35	0.71
NC	4.28	0.23	2.10	-1.00	-1.37	0.47	0.00	-0.22	0.11
NW	6.26	0.22	2.00	-1.12	-0.83	0.12	-0.59	-0.44	0.47
WC	5.51	0.55	2.49	-2.55	-0.10	-0.13	-0.33	-0.23	-

EC, Eastern Cape; FS, Free State; GT, Gauteng; KZ, KwaZulu-Natal; LM, Limpopo; MP, Mpumalanga; NC, Northern Cape; NW, North West; WC, Western Cape.



ART, antiretroviral treatment.

FIGURE 1: Calibration of model to reported numbers of public sector antiretroviral treatment patients, by province: (a) Eastern Cape; (b) Free State; (c) Gauteng; (d) KwaZulu-Natal; (e) Limpopo; (f) Mpumalanga; (g) Northern Cape; (h) North West; (i) Western Cape.

Step 3: Bayesian uncertainty analysis of paediatric numbers

This uncertainty analysis is similar to that in Step 2. The prior distributions for the paediatric ART changes are the same as those for adults and children combined (i.e. the priors for $u_j^1(p)$ are the same as those for $u_j^0(p)$, for j = 2 to 8), but the $B_1^1(p)$ parameter has a normal prior with a mean of 3.58 and a standard deviation of 1.06. This means that even though the paediatric ART initiates are lower than total ART initiates initially, *a priori* we expect the trend in paediatric ART enrolment (on the natural log scale) to be similar to that in adult ART enrolment. (Fitting B-splines to the initial paediatric estimates in Step 1 yields regression coefficients roughly consistent with those in Step 2, on average, when comparing the $u_j^0(p)$ and $u_j^1(p)$ terms.) No prior distribution is specified for the $\exp(-\vartheta_p)$ in Step 3; instead we fix this parameter at the posterior mean from Step 2 to ensure approximate consistency in the interpretation of reported public sector ART statistics in province p.

Having sampled values of $B_1^1(p), u_2^1(p), \ldots, u_8^1(p)$, we calculate the numbers of children starting ART using similar formulas to those in Step 2:

$$S_2^3(2000,p) = \exp\left(B_1^1(p)\right)$$

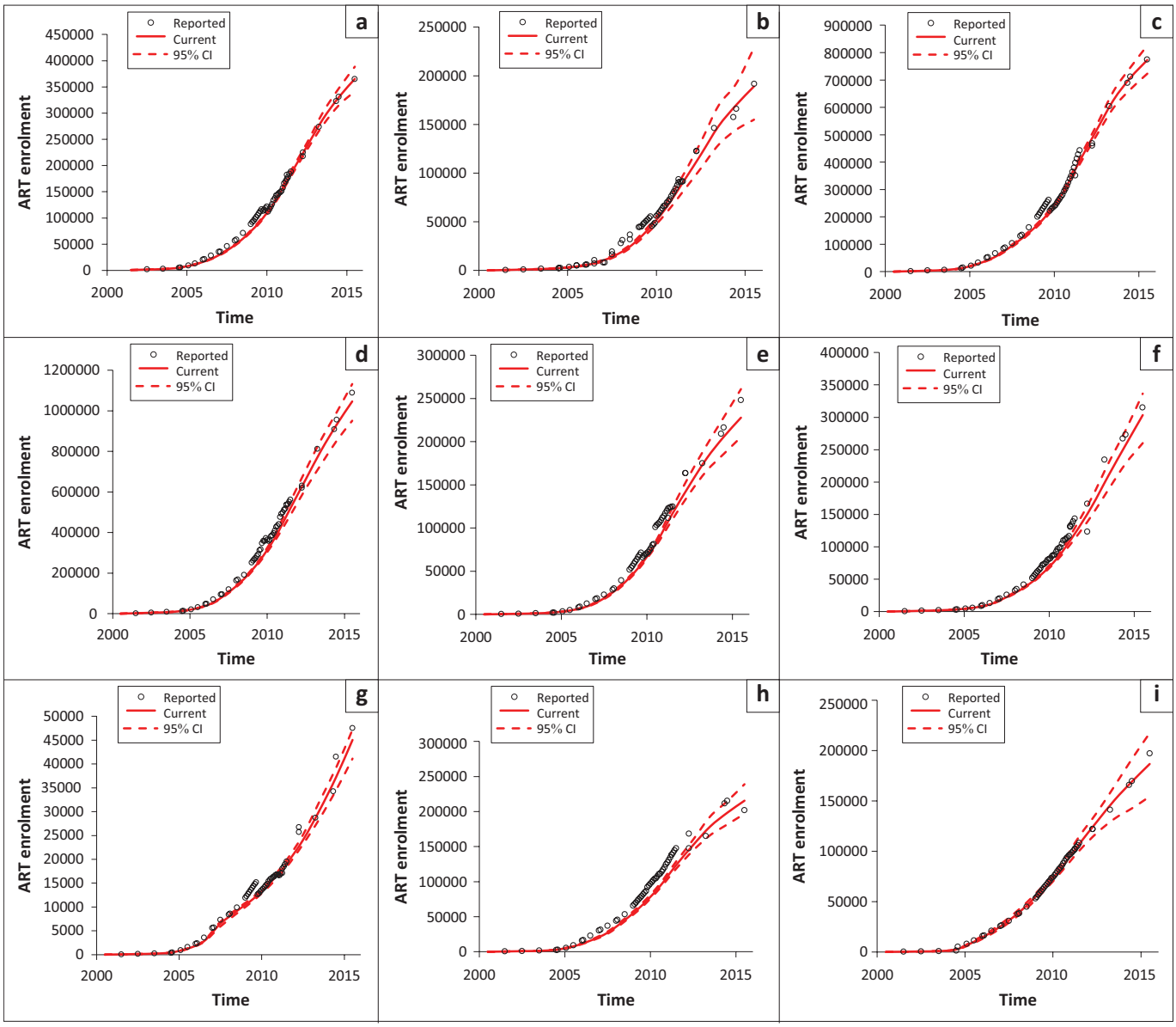
$$S_2^3(2001,p) = \exp\left(B_1^1(p) + 0.5u_2^1(p)\right)$$

$$S_2^3(2002,p) = \exp\left(B_1^1(p) + u_2^1(p)\right)$$

$$S_2^3(2003,p) = \exp\left(B_1^1(p) + u_2^1(p) + 0.5u_3^1(p)\right)$$

...

$$S_2^3(2014,p) = \exp\left(B_1^1(p) + \sum_{j-2}^{8} u_j^1(p)\right) \quad \text{[Eqn 14]}$$



ART, antiretroviral treatment.

FIGURE 2: Posterior estimates of current antiretroviral treatment enrolment compared with reported antiretroviral treatment totals (adults and children combined): (a) Eastern Cape; (b) Free State; (c) Gauteng; (d) KwaZulu-Natal; (e) Limpopo; (f) Mpumalanga; (g) Northern Cape; (h) North West; (i) Western Cape.

We set the Step 3 estimate of the total number of patients starting ART equal to the posterior mean estimated from Step 2, that is, $S^3(t, p)=S^2(t, p)$ for all t. Then the adult male estimates are obtained using the formula

$$S_0^3(t,p)=\left(S^3(t,p)-S_2^3(t,p)\right)\frac{S_0^2(t,p)}{S_0^2(t,p)+S_1^2(t,p)}, \qquad \text{[Eqn 15]}$$

and similarly the adult female ART initiates are calculated as

$$S_1^3(t,p)=\left(S^3(t,p)-S_2^3(t,p)\right)\frac{S_1^2(t,p)}{S_0^2(t,p)+S_1^2(t,p)}. \qquad \text{[Eqn 16]}$$

The likelihood function is calculated in the same way as before, except that the likelihood is defined with respect to reported numbers of children receiving ART.

Table 2 shows the posterior mean estimates for each of the model parameters, compared with the prior means.

Figure 3 shows the model fit to the reported numbers of ART patients (only the model estimates of current enrolment are shown). In most provinces, reporting of paediatric ART totals is very erratic, and as a result confidence intervals around the model estimates are very wide, especially in Free State, Northern Cape and Western Cape.

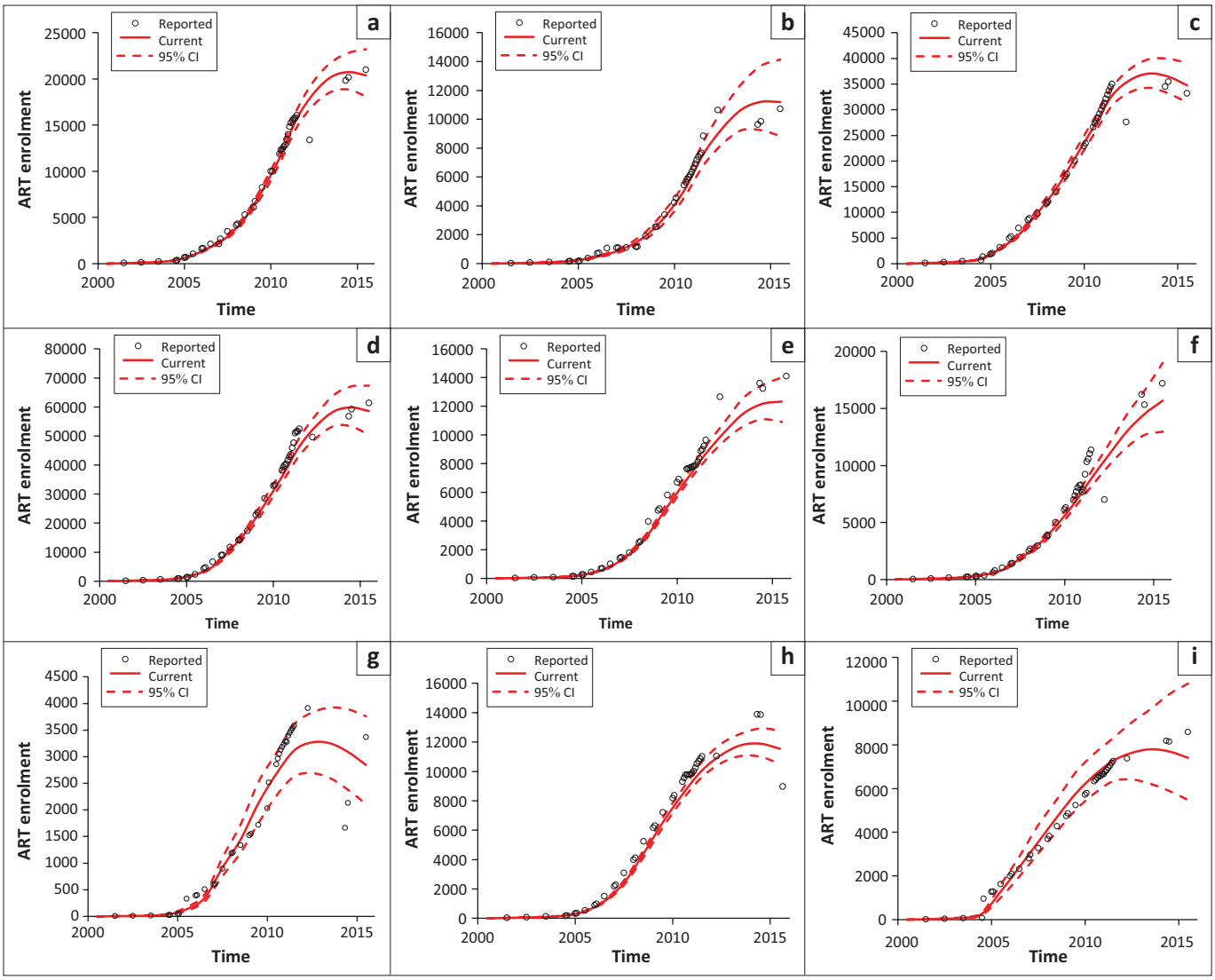
Additional results: Calibration to HIV testing data

Figure 4 shows the annual numbers of HIV tests performed in each province. The model is in close agreement with the estimates derived from public and private data sources. In all provinces, there were substantial increases in HIV testing numbers around 2010, following the introduction of a national HIV testing campaign.

TABLE 2: Prior and posterior means for Step 3 (children only).

Parameter	$B_1^0(p)$	$u_2^0(p)$	$u_3^0(p)$	$u_4^0(p)$	$u_5^0(p)$	$u_6^0(p)$	$u_7^0(p)$	$u_8^0(p)$
Prior mean	3.58	0.45	1.39	-0.76	-0.35	-0.35	-0.35	-0.35
Posterior mean								
EC	4.00	0.36	1.67	-1.17	0.00	-0.41	-0.93	-0.35
FS	3.27	0.33	1.36	-0.70	0.07	-0.35	-1.09	-0.46
GT	4.75	0.43	2.02	-1.77	-0.17	-0.36	-0.99	-0.43
KZ	4.98	0.30	1.68	-0.53	-0.88	-0.28	-0.64	-0.40
LM	3.16	0.34	1.65	-0.49	-0.83	-0.60	-0.18	-0.49
MP	3.62	0.28	1.14	0.14	-0.83	-0.30	-0.36	-0.26
NC	1.37	0.51	2.18	-1.13	-0.96	-0.79	-0.69	-0.35
NW	3.44	0.28	1.75	-0.24	-1.58	-0.35	-0.33	-0.44
WC	2.88	0.74	2.59	-3.09	-0.26	-0.23	-0.30	-0.32

EC, Eastern Cape; FS, Free State; GT, Gauteng; KZ, KwaZulu-Natal; LM, Limpopo; MP, Mpumalanga; NC, Northern Cape; NW, North West; WC, Western Cape.



ART, antiretroviral treatment.

FIGURE 3: Posterior estimates of current antiretroviral treatment enrolment compared with reported antiretroviral treatment totals (children only): (a) Eastern Cape; (b) Free State; (c) Gauteng; (d) KwaZulu-Natal; (e) Limpopo; (f) Mpumalanga; (g) Northern Cape; (h) North West; (i) Western Cape.

FIGURE 4: Annual number of HIV tests performed: (a) Eastern Cape; (b) Free State; (c) Gauteng; (d) KwaZulu-Natal; (e) Limpopo; (f) Mpumalanga; (g) Northern Cape; (h) North West; (i) Western Cape.

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