Supporting information for Multiple imputation for harmonizing longitudinal non-commensurate measures in individual participant data meta-analysis

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B OpenBUGS code

```
model {
    for(i in 1:NOBS){
    z[i, 1:2] ~ dmnorm(z.hat[i, 1:2], omega[,])
    z.hat[i,1] <- B[id[i], 1] + B[id[i], 2]*(day[i]-mean(day[])) + beta1.c*sex[i] +
                  beta2.c*(age[i] - mean(age[])) + beta3.c*tx[i] +
                  beta4.c*tx[i]*(day[i]-mean(day[]))  #cdrs
    z.hat[i,2] <- B[id[i], 3] + B[id[i], 4]*(day[i]-mean(day[])) + beta1.h*sex[i] +
                  beta2.h*(age[i] - mean(age[])) + beta3.h*tx[i] +
                  beta4.h*tx[i]*(day[i]-mean(day[]))  #hdrs
       }

omega[1:2,1:2] ~ dwish(R[,],2)
R[1,1] <- 1
R[2,2] <- 1
R[1,2] <- 0
R[2,1] <- 0
V[1:2,1:2] <- inverse(omega[,])
beta1.c ~ dnorm (0.0, .0001)
beta2.c ~ dnorm (0.0, .0001)
```

```
beta3.c ~ dnorm (0.0, .0001)
beta4.c ~ dnorm (0.0, .0001)
beta1.h ~ dnorm (0.0, .0001)
beta2.h ~ dnorm (0.0, .0001)
beta3.h ~ dnorm (0.0, .0001)
beta4.h ~ dnorm (0.0, .0001)

  for (j in 1:J){
    for (k in 1:K){
      B[j,k] <- B.raw[j,k]
    }
    B.raw[j,1:K] ~ dmnorm (mu.raw[], Tau.B.raw[,])
  }
  for (k in 1:K){
    mu[k] <- mu.raw[k]
    mu.raw[k] ~ dnorm (0, .0001)
  }
  Tau.B.raw[1:K,1:K] ~ dwish(W[,], df)
  df <- K + 2
  Sigma.B.raw[1:K,1:K] <- inverse(Tau.B.raw[,])
  for (k in 1:K){
    for (k.prime in 1:K){
      rho.B[k,k.prime] <- Sigma.B.raw[k,k.prime]/
        sqrt(Sigma.B.raw[k,k]*Sigma.B.raw[k.prime,k.prime])
    }
    sigma.B[k] <- sqrt(Sigma.B.raw[k,k])
  }
}
```

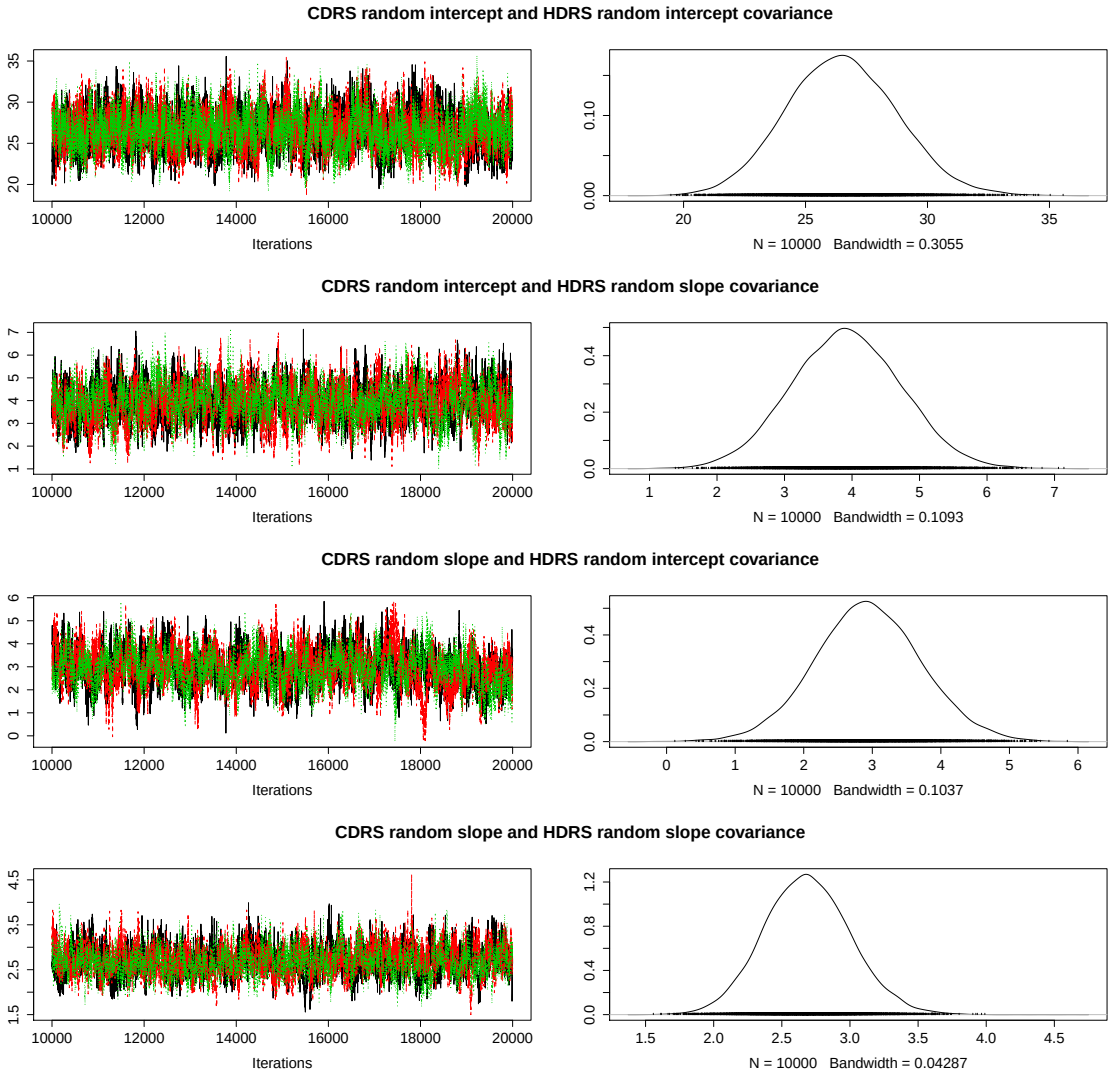
C Trace plots and density plots for parameters from the random effects variance-covariance matrix

The key parameters in the random-effects variance-covariance matrix of the imputation model are the covariances across scales, that is:

- The covariance of the CDRS random intercept and the HDRS random intercept
- The covariance of the CDRS random intercept and the HDRS random slope

- The covariance of the CDRS random slope and the HDRS random intercept
- The covariance of the CDRS random slope and the HDRS random slope

Figure 1: Trace plots (based on 3 MCMC chains) and density plots for 4 key parameters from the variance-covariance matrix of the random effects in the imputation model. Plots are the result of 10,000 MCMC iterations after a 10,000 iteration burn-in. Gelman-Rubin statistics for all 4 parameters were equal to 1



These 4 parameters, along with the covariance of the error terms, determine the covariance between the HDRS and CDRS and its change over time. Therefore, these are the key

parameters in terms of generating accurate imputations. Figure 1 presents trace plots (based on 3 MCMC chains) as well as density plots from 10,000 MCMC iterations (after a 10,000 iteration burn-in period).

As can be seen, there is good mixing among chains and posterior densities are smooth and unimodal. Further, Gelman-Rubin statistics for all 4 parameters were equal to 1. These diagnostics suggest that these parameters are identifiable and well-estimated.

D Post-imputation analyses without the use of a calibration sample

Table 1: Observed-only and post-imputation analyses of CDRS and HDRS scores in fluoxetine trials. Here, the imputed values are generated without using the calibration data. The observed-only HDRS analysis is based on a single trial and does not include a random effect at the trial level. All other models include trial-specific random effects.

		Observed				Imputed w/out calibration			
Outcome	Parameter	Est	SE	t-val	p-val	Est	SE	t-val	p-val
	Intercept	54.00	2.56	21.12	<.001	54.54	2.12	25.67	<.001
	Time	-3.79	0.18	-21.34	<.001	-3.80	0.17	-21.89	<.001
	Tx*Time	-1.06	0.21	-4.92	<.001	-1.06	0.21	-5.07	<.001
CDRS	SD(b_{0l})	5.03				4.57			
	SD(b_{0i})	9.91				9.86			
	SD(b_{1i})	2.52				2.44			
	Corr(b_{0i}, b_{1i})	-0.46				-0.45			
	SD(ε_{ijl})	7.23				7.31			
	Intercept	22.59	0.67	33.48	<.001	19.75	1.63	12.11	<.001
	Time	-3.34	0.42	-7.87	<.001	-3.27	0.29	-11.39	<.001
	Tx*Time	-0.57	0.55	-1.03	.308	-0.40	0.30	-1.34	.182
HDRS	SD(b_{0l})	NA				1.81			
	SD(b_{0i})	2.11				5.54			
	SD(b_{1i})	1.46				0.69			
	Corr(b_{0i}, b_{1i})	0.13				-0.68			
	SD(ε_{ijl})	3.97				3.95			

SD(b_{0l}): Standard deviation of random trial-level intercepts
SD(b_{0i}): Standard deviation of random subject-level intercepts
SD(b_{1i}): Standard deviation of random subject-level slopes
Corr(b_{0i}, b_{1i}): Correlation of random intercepts and slopes
SD(ε_{ijl}): Standard deviation of residual error

E Partial correlations in calibration sample by treatment group

Table 2: Partial correlation by treatment group and study (controlling for age and gender) between CDRS and HDRS in the calibration sample.

	Study 1		Study 2		Overall	
Week	Control	Treatment	Control	Treatment	Control	Treatment
0	0.68	0.77	0.39	0.62	0.51	0.65
1	0.74	0.76	0.59	0.64	0.67	0.65
2	0.78	0.78	0.71	0.77	0.73	0.75
3	0.81	0.82	0.74	0.77	0.76	0.77
4	0.83	0.85	0.79	0.76	0.81	0.78
6	0.86	0.84	0.77	0.80	0.81	0.80
8	0.88	0.82	0.84	0.79	0.85	0.80