

bayes options

```
. bayes, mcmcsize(20000) rseed(15): regress sbp age sex, noheader
```

Burn-in ...

Simulation ...

		Mean	Std. Dev.	MCSE	Median	Equal-tailed [95% Cred. Interval]	
sbp	age	.6534317	.0114105	.000255	.6536947	.6307121	.6759597
	sex	-4.00721	.3937663	.009617	-3.996228	-4.792526	-3.228289
	_cons	105.9069	.8296369	.020308	105.9145	104.2994	107.5164
	sigma2	414.5079	5.787044	.08457	414.3449	403.5459	426.0861

bayes options

```
. bayes, prior({sbp:_cons}, uniform(0,100000)): regress sbp age sex, noheader
```

Burn-in ...

Simulation ...

		Mean	Std. Dev.	MCSE	Median	Equal-tailed [95% Cred. Interval]	
sbp	age	.6540455	.0114258	.001014	.6539745	.6307604	.6773937
	sex	-3.98343	.4274413	.057665	-3.977014	-4.817774	-3.161497
	_cons	105.8344	.8795776	.134451	105.8031	104.0552	107.5987
	sigma2	414.7011	5.908955	.125499	414.755	403.4261	426.1227

bayes options

```
. bayes, prior({sbp:}, flat) rseed(15): regress sbp age sex, noheader
```

Burn-in ...

Simulation ...

		Mean	Std. Dev.	MCSE	Median	Equal-tailed [95% Cred. Interval]	
sbp	age	.6526178	.0116337	.000381	.6526526	.6298636	.6755101
	sex	-3.980036	.3999808	.015065	-3.978874	-4.783137	-3.175131
	_cons	105.9061	.8540208	.031618	105.9191	104.1937	107.601
sigma2		414.6034	5.89807	.12075	414.6523	403.5478	426.3987

Checking “Convergence” of the Chain

- Effective Sample Size
- Trace Plots
- Histograms
- Correlegrams
- Scatterplot Matrices

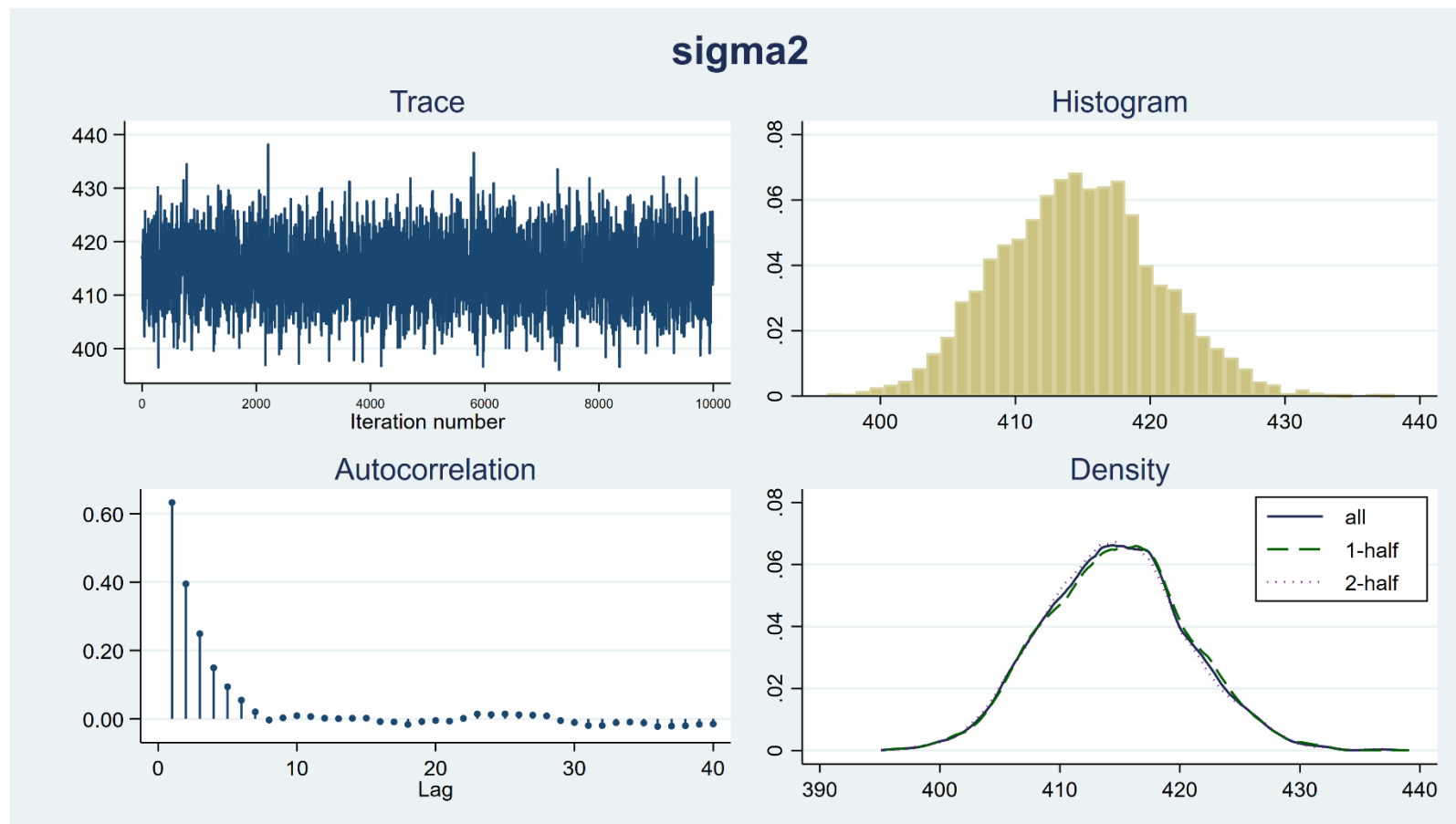
Checking “Convergence” of the Chain

```
. bayesstats ess
```

Efficiency summaries MCMC sample size = 10,000

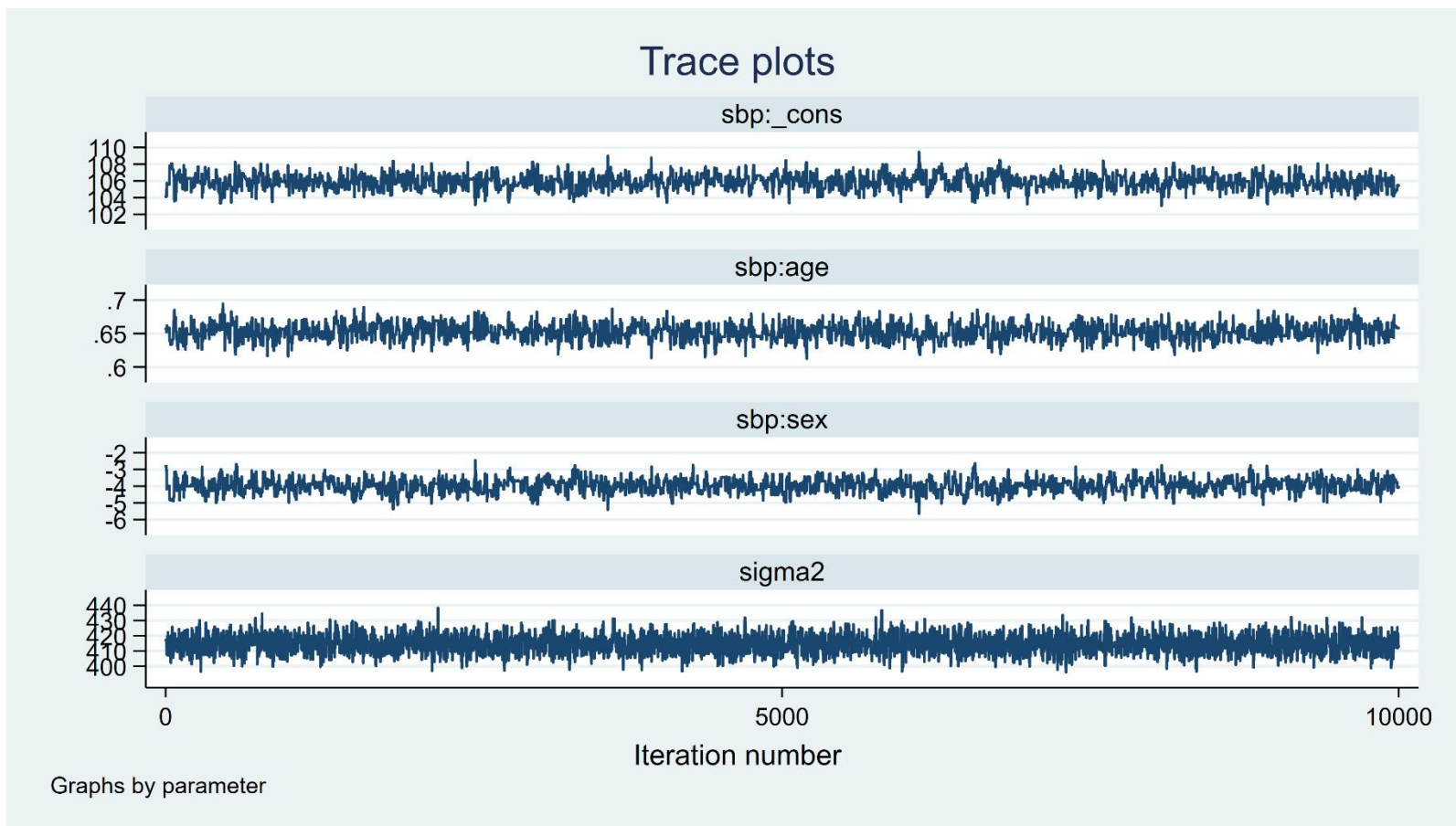
		ESS	Corr. time	Efficiency
sbp	age	931.42	10.74	0.0931
	sex	704.95	14.19	0.0705
	_cons	729.56	13.71	0.0730
sigma2		2385.86	4.19	0.2386

Checking “Convergence” of the Chain



```
bayesgraph diagnostics {sigma2}
```

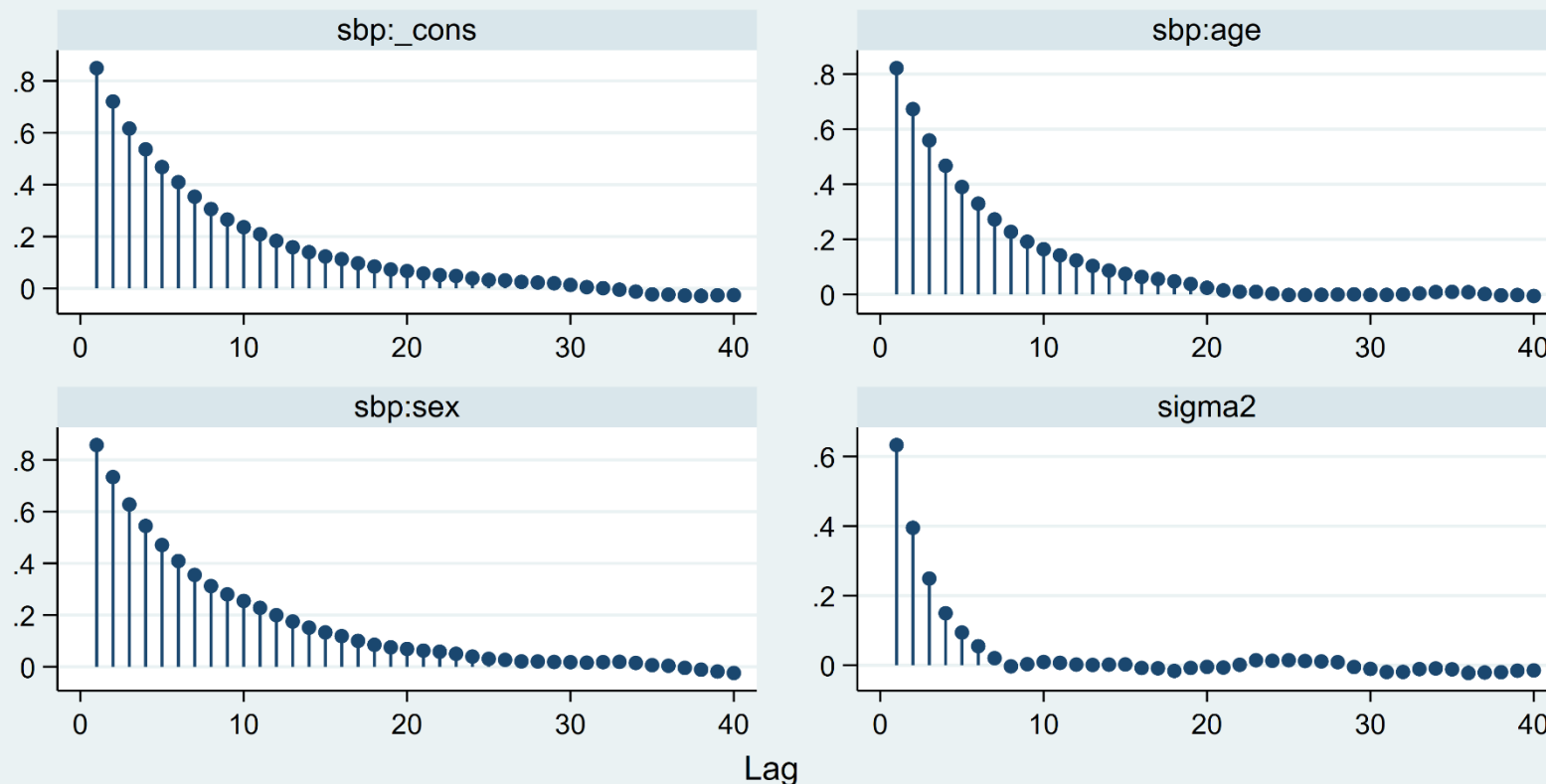
Checking “Convergence” of the Chain



```
bayesgraph trace {sbp: _cons age sex} {sigma2}, byparm
```

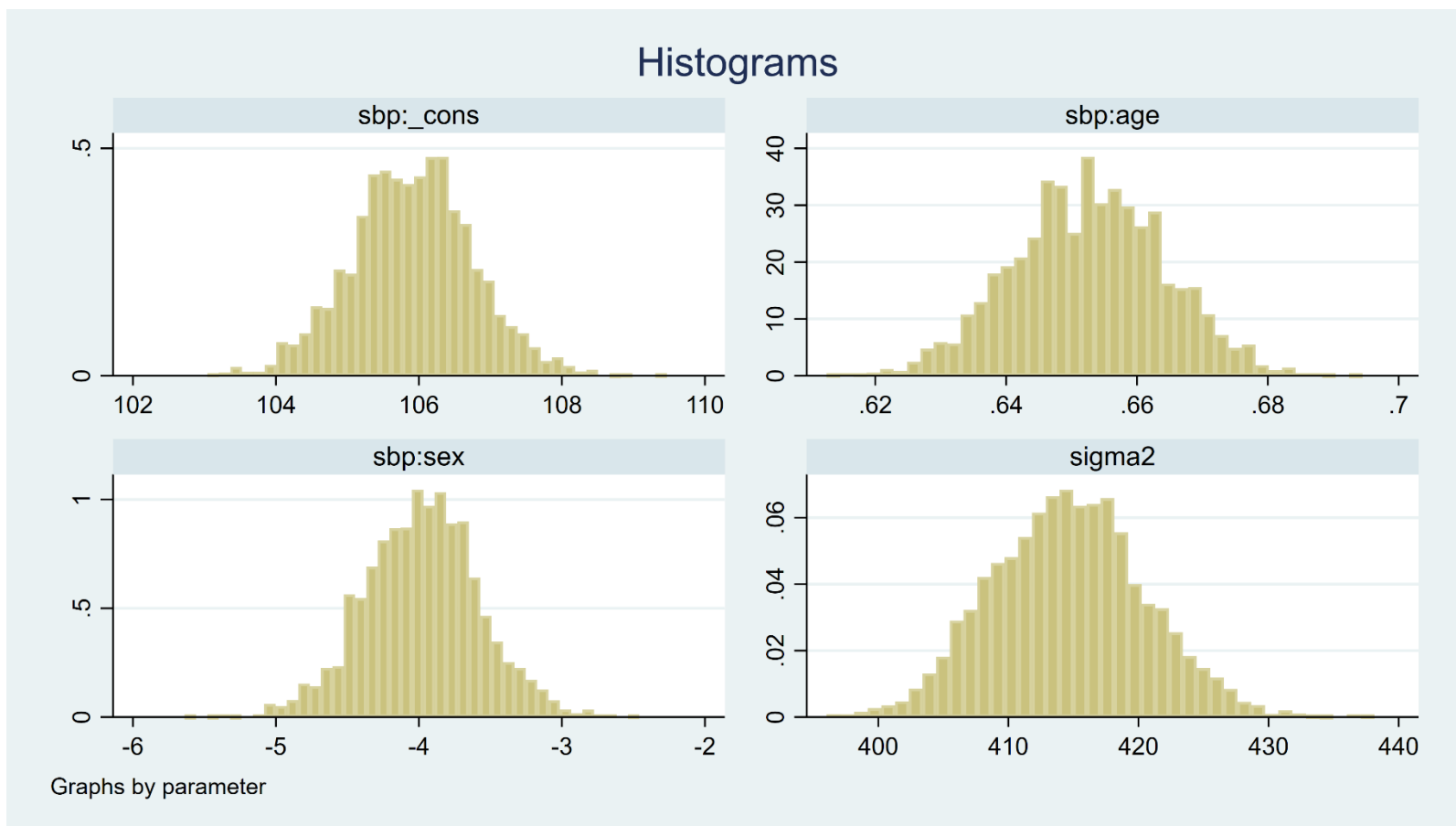
Checking “Convergence” of the Chain

Autocorrelations



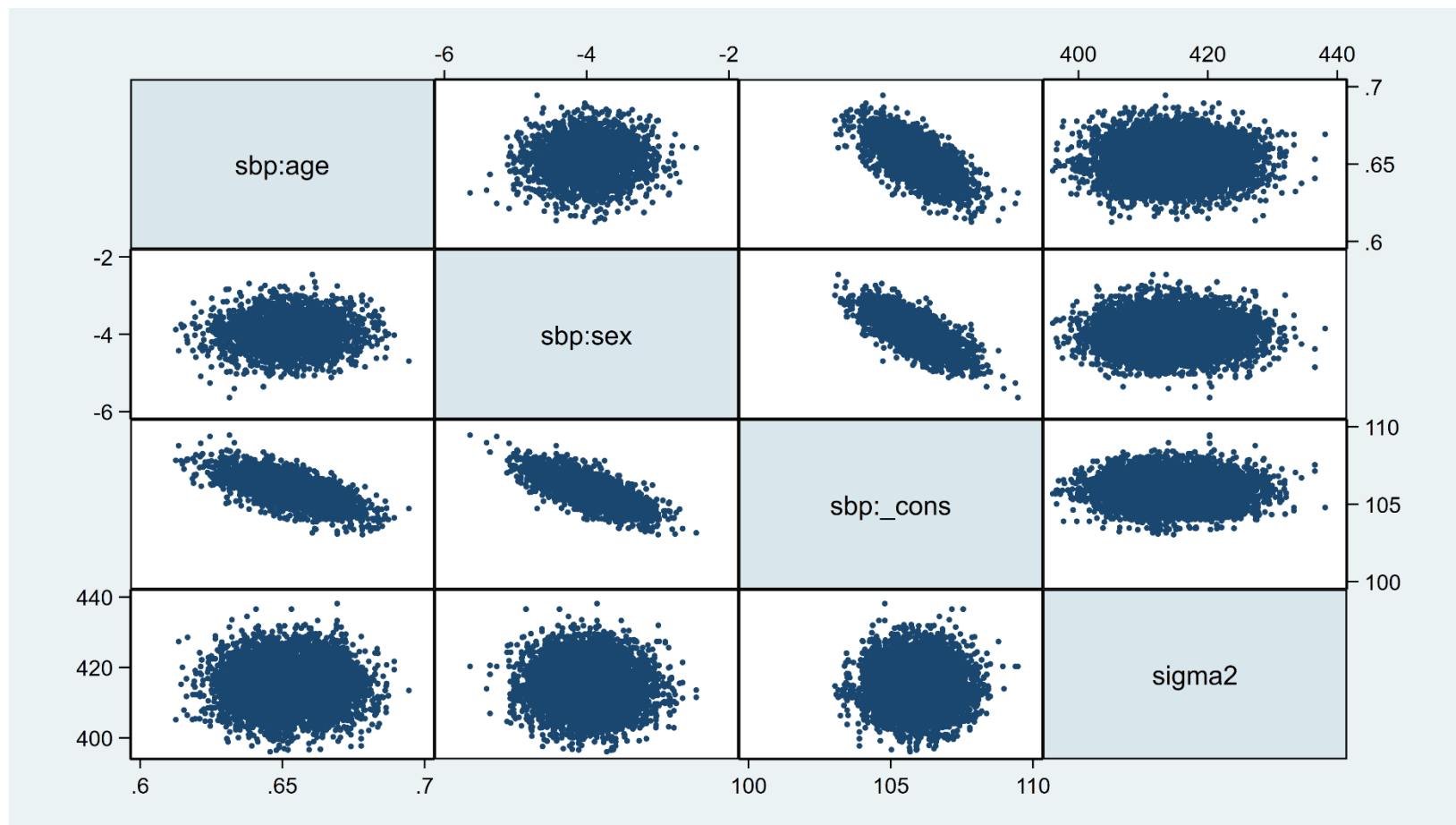
```
bayesgraph ac {sbp: _cons age sex} {sigma2}, byparm
```


Checking “Convergence” of the Chain



```
bayesgraph histogram {sbp: _cons age sex} {sigma2}, byparm
```

Checking “Convergence” of the Chain



```
bayesgraph matrix _all
```

Bayesian Model Selection

```
quietly {  
    bayes, rseed(15): regress sbp age  
    estimates store age  
  
    bayes, rseed(15): regress sbp sex  
    estimates store sex  
  
    bayes, rseed(15): regress sbp age sex  
    estimates store full  
}
```

Bayesian Model Selection

```
. bayesstats ic age sex full, diconly
```

Deviance information criterion

	DIC
age	91863.22
sex	94518.91
full	91765.08

Bayesian Model Selection

```
. bayestest model age sex full
```

Bayesian model tests

	log (ML)	P (M)	P (M y)
age	-4.60e+04	0.3333	0.0000
sex	-4.73e+04	0.3333	0.0000
full	-4.59e+04	0.3333	1.0000

Note: Marginal likelihood (ML) is computed using Laplace-Metropolis approximation.

Tests

```
. bayestest interval {sbp:sex}, lower(-4.5) upper(-3.5)
```

```
Interval tests      MCMC sample size =      10,000
```

```
prob1 : -4.5 < {sbp:sex} < -3.5
```

	Mean	Std. Dev.	MCSE
prob1	.7973	0.40203	.0119621

Predictions

Frequentist

```
. lincom _b[_cons] + _b[age]*40 + _b[sex]*1
```

```
( 1)  40*age + sex + _cons = 0
```

sbp	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
(1)	128.0394	.3029431	422.65	0.000	127.4455	128.6332

Bayesian

```
. bayesstats summary (predicted: {sbp:_cons} + {sbp:age}*40 + {sbp:sex}*1)
```

Posterior summary statistics

MCMC sample size = 10,000

```
predicted : {sbp:_cons} + {sbp:age}*40 + {sbp:sex}*1
```

	Mean	Std. Dev.	MCSE	Median	Equal-tailed [95% Cred. Interval]	
predicted	128.0308	.302904	.010543	128.0302	127.4152	128.626

Predictions

```
. bayesstats summary (pred20: {sbp: cons} + {sbp:age}*20 + {sbp:sex}*1)   ///
>                    (pred30: {sbp:_cons} + {sbp:age}*30 + {sbp:sex}*1)   ///
>                    (pred40: {sbp:_cons} + {sbp:age}*40 + {sbp:sex}*1)   ///
>                    (pred50: {sbp:_cons} + {sbp:age}*50 + {sbp:sex}*1)   ///
>                    (pred60: {sbp:_cons} + {sbp:age}*60 + {sbp:sex}*1)
```

Posterior summary statistics

MCMC sample size = 10,000

```
pred20 : {sbp:_cons} + {sbp:age}*20 + {sbp:sex}*1
pred30 : {sbp:_cons} + {sbp:age}*30 + {sbp:sex}*1
pred40 : {sbp:_cons} + {sbp:age}*40 + {sbp:sex}*1
pred50 : {sbp:_cons} + {sbp:age}*50 + {sbp:sex}*1
pred60 : {sbp:_cons} + {sbp:age}*60 + {sbp:sex}*1
```

	Mean	Std. Dev.	MCSE	Median	Equal-tailed [95% Cred. Interval]	
pred20	114.9784	.4379494	.015753	114.9799	114.1189	115.8346
pred30	121.5046	.3581074	.012855	121.502	120.7835	122.2075
pred40	128.0308	.302904	.010543	128.0302	127.4152	128.626
pred50	134.5569	.2869309	.009281	134.5559	133.9835	135.1318
pred60	141.0831	.3161906	.009505	141.0871	140.4444	141.7132


```
. bayesstats summary (pred20_m: {sbp:_cons} + {sbp:age}*20 + {sbp:sex}*1)      ///
>                    (pred30_m: {sbp:_cons} + {sbp:age}*30 + {sbp:sex}*1)      ///
>                    (pred40_m: {sbp:_cons} + {sbp:age}*40 + {sbp:sex}*1)      ///
>                    (pred50_m: {sbp:_cons} + {sbp:age}*50 + {sbp:sex}*1)      ///
>                    (pred60_m: {sbp:_cons} + {sbp:age}*60 + {sbp:sex}*1)      ///
>                    (pred20_f: {sbp:_cons} + {sbp:age}*20 + {sbp:sex}*0)      ///
>                    (pred30_f: {sbp:_cons} + {sbp:age}*30 + {sbp:sex}*0)      ///
>                    (pred40_f: {sbp:_cons} + {sbp:age}*40 + {sbp:sex}*0)      ///
>                    (pred50_f: {sbp:_cons} + {sbp:age}*50 + {sbp:sex}*0)      ///
>                    (pred60_f: {sbp:_cons} + {sbp:age}*60 + {sbp:sex}*0)
```

Posterior summary statistics

MCMC sample size = 10,000

```
pred20_m : {sbp:_cons} + {sbp:age}*20 + {sbp:sex}*1
pred30_m : {sbp:_cons} + {sbp:age}*30 + {sbp:sex}*1
pred40_m : {sbp:_cons} + {sbp:age}*40 + {sbp:sex}*1
pred50_m : {sbp:_cons} + {sbp:age}*50 + {sbp:sex}*1
pred60_m : {sbp:_cons} + {sbp:age}*60 + {sbp:sex}*1
pred20_f : {sbp:_cons} + {sbp:age}*20 + {sbp:sex}*0
pred30_f : {sbp:_cons} + {sbp:age}*30 + {sbp:sex}*0
pred40_f : {sbp:_cons} + {sbp:age}*40 + {sbp:sex}*0
pred50_f : {sbp:_cons} + {sbp:age}*50 + {sbp:sex}*0
pred60_f : {sbp:_cons} + {sbp:age}*60 + {sbp:sex}*0
```

	Mean	Std. Dev.	MCSE	Median	Equal-tailed [95% Cred. Interval]	
pred20_m	114.9784	.4379494	.015753	114.9799	114.1189	115.8346
pred30_m	121.5046	.3581074	.012855	121.502	120.7835	122.2075
pred40_m	128.0308	.302904	.010543	128.0302	127.4152	128.626
pred50_m	134.5569	.2869309	.009281	134.5559	133.9835	135.1318
pred60_m	141.0831	.3161906	.009505	141.0871	140.4444	141.7132
pred20_f	118.9584	.7203004	.026823	118.9762	117.5071	120.3934
pred30_f	125.4846	.673926	.024949	125.497	124.118	126.8576
pred40_f	132.0108	.6454366	.02356	132.0166	130.7125	133.2819
pred50_f	138.537	.6372357	.02273	138.5357	137.2608	139.7823
pred60_f	145.0632	.6500914	.022564	145.0545	143.7583	146.3276

Predictions

```
. return list
```

```
scalars:
```

```
      r(clevel) = 95
        r(hpd) = 0
      r(batch) = 0
      r(skip) = 0
r(corrllag) = 500
r(corrctl) = .01
```

```
macros:
```

```
      r(names) : ""pred20_m" "pred30_m" "pred40_m" "pred50_m" "pred60_m" "pred20.."
r(exprnames) : ""pred20_m" "pred30_m" "pred40_m" "pred50_m" "pred60_m" "pred20.."
r(expr_10) : "{sbp:_cons} + {sbp:age}*60 + {sbp:sex}*0"
r(expr_9) : "{sbp:_cons} + {sbp:age}*50 + {sbp:sex}*0"
r(expr_8) : "{sbp:_cons} + {sbp:age}*40 + {sbp:sex}*0"
r(expr_7) : "{sbp:_cons} + {sbp:age}*30 + {sbp:sex}*0"
r(expr_6) : "{sbp:_cons} + {sbp:age}*20 + {sbp:sex}*0"
r(expr_5) : "{sbp:_cons} + {sbp:age}*60 + {sbp:sex}*1"
r(expr_4) : "{sbp:_cons} + {sbp:age}*50 + {sbp:sex}*1"
r(expr_3) : "{sbp:_cons} + {sbp:age}*40 + {sbp:sex}*1"
r(expr_2) : "{sbp:_cons} + {sbp:age}*30 + {sbp:sex}*1"
r(expr_1) : "{sbp:_cons} + {sbp:age}*20 + {sbp:sex}*1"
```

```
matrices:
```

```
      r(summary) : 10 x 6
```

Predictions

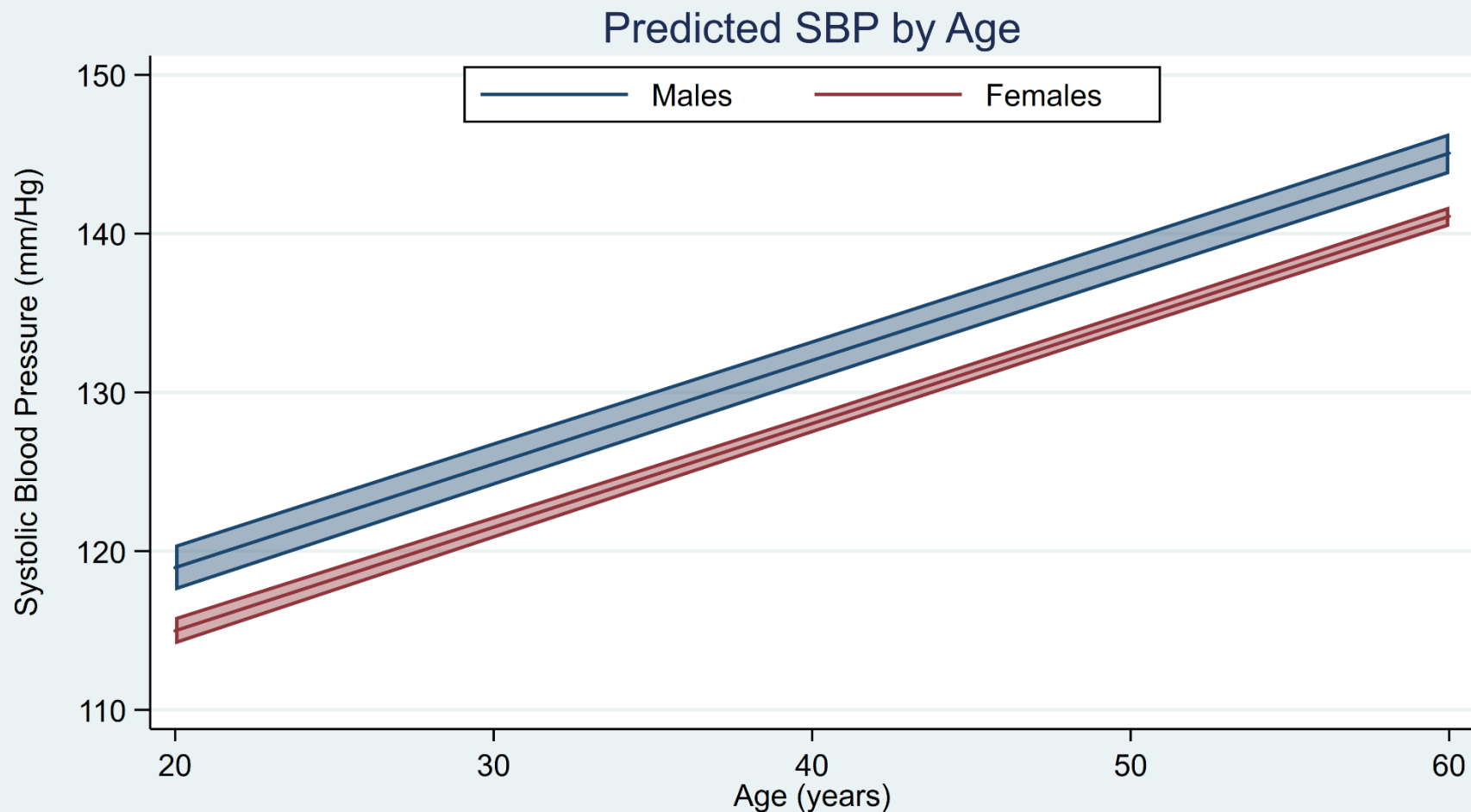
```
. matlist r(summary)
```

	Mean	Std Dev	MCSE	Median	CrI lower	CrI upper
pred20_m	114.9784	.4379494	.0157533	114.9799	114.1189	115.8346
pred30_m	121.5046	.3581074	.0128547	121.502	120.7835	122.2075
pred40_m	128.0308	.302904	.0105433	128.0302	127.4152	128.626
pred50_m	134.5569	.2869309	.0092808	134.5559	133.9835	135.1318
pred60_m	141.0831	.3161906	.009505	141.0871	140.4444	141.7132
pred20_f	118.9584	.7203004	.0268228	118.9762	117.5071	120.3934
pred30_f	125.4846	.673926	.0249485	125.497	124.118	126.8576
pred40_f	132.0108	.6454366	.0235596	132.0166	130.7125	133.2819
pred50_f	138.537	.6372357	.0227302	138.5357	137.2608	139.7823
pred60_f	145.0632	.6500914	.0225638	145.0545	143.7583	146.3276

Convert the Matrix to a Dataset

```
matrix pred = r(summary)
clear
svmat pred          /* convert matrix to dataset */
rename pred1 mean
rename pred2 stddev
rename pred3 mcse
rename pred4 median
rename pred5 lower
rename pred6 upper
gen sex = _n<6
label define sex 0 "Female" 1 "Male"
label values sex sex
gen age = (_n+1)*10 if _n<6
replace age = (_n-4)*10 if _n>5
```

Predictions



The **bayes** Prefix

Linear regression models

regress	[BAYES] bayes: regress	Linear regression
hetregress	[BAYES] bayes: hetregress	Heteroskedastic linear regressions
tobit	[BAYES] bayes: tobit	Tobit regression
intreg	[BAYES] bayes: intreg	Interval regression
truncreg	[BAYES] bayes: truncreg	Truncated regression
mvreg	[BAYES] bayes: mvreg	Multivariate regression

Sample-selection regression models

heckman	[BAYES] bayes: heckman	Heckman selection model
heckprobit	[BAYES] bayes: heckprobit	Probit model with sample selection
heckoprobit	[BAYES] bayes: heckoprobit	Ordered probit model with sample selection

The **bayes** Prefix

Binary-response regression models

logistic	[BAYES]	bayes: logistic	Logistic regression, reporting odds ratios
logit	[BAYES]	bayes: logit	Logistic regression, reporting coefficients
probit	[BAYES]	bayes: probit	Probit regression
cloglog	[BAYES]	bayes: cloglog	Complementary log-log regression
hetprobit	[BAYES]	bayes: hetprobit	Heteroskedastic probit regressions
binreg	[BAYES]	bayes: binreg	GLM for the binomial family
biprobit	[BAYES]	bayes: biprobit	Bivariate probit regression

Ordinal-response regression models

ologit	[BAYES]	bayes: ologit	Ordered logistic regression
oprobit	[BAYES]	bayes: oprobit	Ordered probit regression
zioprobit	[BAYES]	bayes: zioprobit	Zero-inflated ordered probit regression

Categorical-response regression models

mlogit	[BAYES]	bayes: mlogit	Multinomial (polytomous) logistic regression
mprobit	[BAYES]	bayes: mprobit	Multinomial probit regression
clogit	[BAYES]	bayes: clogit	Conditional logistic regression

The **bayes** Prefix

Count-response regression models

poisson	[BAYES] bayes: poisson	Poisson regression
nbreg	[BAYES] bayes: nbreg	Negative binomial regression
gnbreg	[BAYES] bayes: gnbreg	Generalized negative binomial regression
tpoisson	[BAYES] bayes: tpoisson	Truncated Poisson regression
tnbreg	[BAYES] bayes: tnbreg	Truncated negative binomial regression
zip	[BAYES] bayes: zip	Zero-inflated Poisson regression
zinb	[BAYES] bayes: zinb	Zero-inflated negative binomial regression

Generalized linear models

glm	[BAYES] bayes: glm	Generalized linear models
------------	---------------------------	---------------------------

Fractional-response regression models

fracreg	[BAYES] bayes: fracreg	Fractional response regression
betareg	[BAYES] bayes: betareg	Beta regression

Survival regression models

streg	[BAYES] bayes: streg	Parametric survival models
--------------	-----------------------------	----------------------------

The **bayes** Prefix

Multilevel regression models

mixed	[BAYES]	bayes: mixed	Multilevel linear regression
metobit	[BAYES]	bayes: metobit	Multilevel tobit regression
meintreg	[BAYES]	bayes: meintreg	Multilevel interval regression
melogit	[BAYES]	bayes: melogit	Multilevel logistic regression
meprobit	[BAYES]	bayes: meprobit	Multilevel probit regression
mecloglog	[BAYES]	bayes: mecloglog	Multilevel complementary log-log regression
meologit	[BAYES]	bayes: meologit	Multilevel ordered logistic regression
meoprobit	[BAYES]	bayes: meoprobit	Multilevel ordered probit regression
mepoisson	[BAYES]	bayes: mepoisson	Multilevel Poisson regression
menbreg	[BAYES]	bayes: menbreg	Multilevel negative binomial regression
meglm	[BAYES]	bayes: meglm	Multilevel generalized linear model
mestreg	[BAYES]	bayes: mestreg	Multilevel parametric survival regression

Outline

- Introduction to Bayesian Analysis
- Coin Toss Example
- Priors, Likelihoods, and Posteriors
- Markov Chain Monte Carlo (MCMC)
- Bayesian Linear Regression
- **Advantages and Disadvantages of Bayes**

Advantages of Bayesian Statistics

- Formally incorporate prior information into studies
- Works when maximum likelihood estimation (MLE) fails or is not identified
- Does not rely on asymptotic normality like MLE
- Works with small sample sizes
- Intuitive interpretation of results such as credible intervals

US Food and Drug Administration (FDA)

Guidance for Industry and FDA Staff

Guidance for the Use of Bayesian Statistics in Medical Device Clinical Trials

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For questions regarding this document, contact Dr. Greg Campbell (CDRH) at 301-796-5750 or greg.campbell@fda.hhs.gov or the Office of Communication, Outreach and Development, (CBER) at 1-800-835-4709 or 301-827-1800.



U.S. Department of Health and Human Services
Food and Drug Administration
Center for Devices and Radiological Health

Division of Biostatistics
Office of Surveillance and Biometrics



Center for Biologics Evaluation and Research

Incorporating informative prior distributions

A Bayesian analysis of a current study of a new device may include prior information from:

- the new device,
- the control device, or
- both devices.

When incorporating prior information from a previous study, the patients in the previous study are rarely considered exchangeable with the patients in the current study. Instead, a hierarchical model is often used to “borrow strength” from the previous studies. At the first level of the hierarchy, these models assume that patients are exchangeable within a study but not across studies. At a second level of the hierarchy, the previous studies are assumed to be exchangeable with the current study, which acknowledges variation between studies. For more detail on hierarchical models, see Section 4.6.

Quote from page 22

Disadvantages of Bayesian Statistics

- Subjectivity in the selection of prior distributions
- Computational complexity

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Thank you!

Questions?

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