

Problem set 6: Bayesian OLS

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Q1) OLS

```
. reg lwage educ exper smsa black south
```

Source	SS	df	MS	Number of obs	=	3,010
Model	165.205654	5	33.0411308	F(5, 3004)	=	232.21
Residual	427.435957	3,004	.142288934	Prob > F	=	0.0000
				R-squared	=	0.2788
				Adj R-squared	=	0.2776
Total	592.641611	3,009	.196956335	Root MSE	=	.37721

lwage	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
educ	.073807	.0035336	20.89	0.000	.0668784	.0807356
exper	.0393134	.0021955	17.91	0.000	.0350085	.0436183
smsa	.1647411	.0156919	10.50	0.000	.1339732	.195509
black	-.1882225	.0177678	-10.59	0.000	-.2230607	-.1533843
south	-.1290528	.0152285	-8.47	0.000	-.1589122	-.0991935
_cons	4.913331	.0631212	77.84	0.000	4.789566	5.037096

Q2) Bayes using Metropolis-Hastings, use flat prior, plot histograms

a) Bayes Metropolis- Hastings algorithm, using flat prior for all

```
. bayesmh lwage educ exper smsa black south, likelihood(normal({var})) prior({lwage: _cons educ exper smsa black south}, flat) prior({var}, jeffreys)
```

Burn-in ...
Simulation ...

Model summary

Likelihood:

lwage ~ normal(xb_lwage,{var})

Priors:

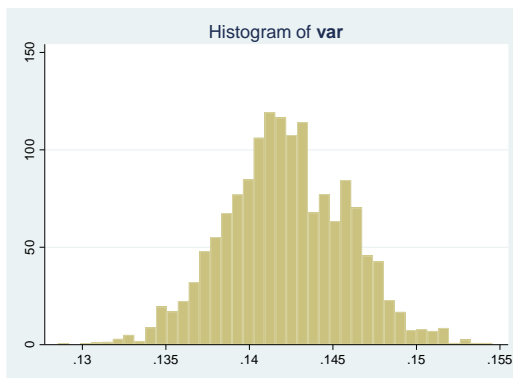
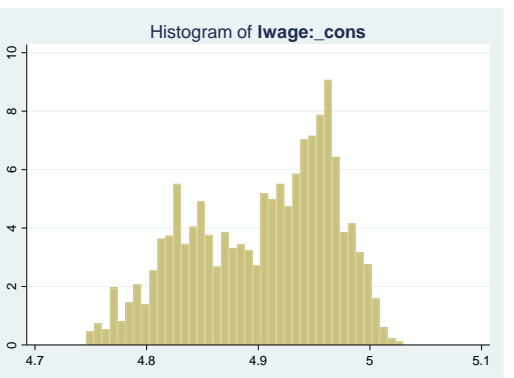
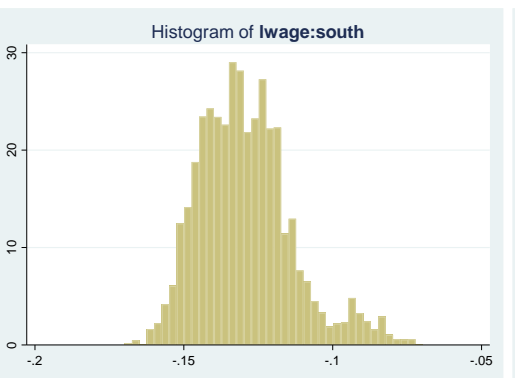
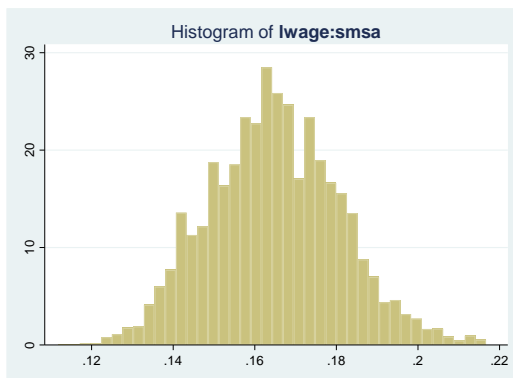
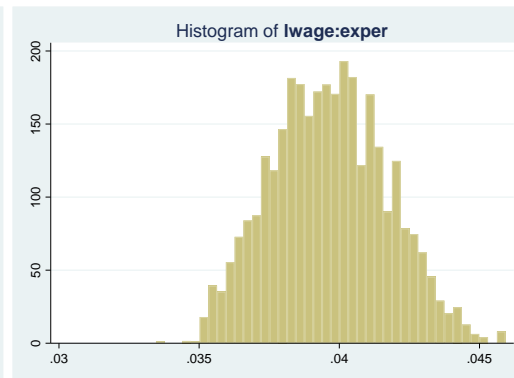
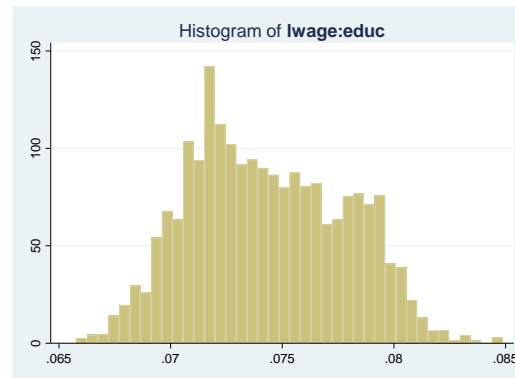
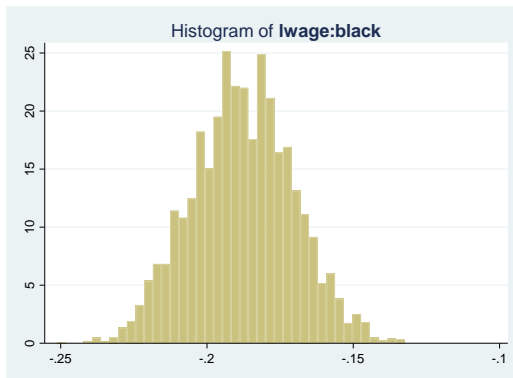
{lwage:_cons educ exper smsa black south} ~ 1 (flat) (1)
{var} ~ jeffreys

(1) Parameters are elements of the linear form xb_lwage.

Bayesian normal regression	MCMC iterations	=	12,500
Random-walk Metropolis-Hastings sampling	Burn-in	=	2,500
	MCMC sample size	=	10,000
	Number of obs	=	3,010
	Acceptance rate	=	.2392
	Efficiency: min	=	.001266
	avg	=	.005404
	max	=	.01671
Log marginal likelihood = -1360.3484			

	Mean	Std. Dev.	MCSE	Median	Equal-tailed	
					[95% Cred. Interval]	
lwage						
educ	.0743258	.0034661	.000904	.0740133	.0683067	.0806296
exper	.039635	.0020627	.000434	.0396168	.0357716	.0437261
smsa	.1647284	.0160211	.00193	.1645684	.1353478	.1966974
black	-.1878744	.0173699	.002068	-.1880804	-.2207895	-.1541442
south	-.1292823	.0156651	.003353	-.1309543	-.1542596	-.0897909
_cons	4.903147	.0634373	.017832	4.915855	4.772623	4.999295
var	.1422125	.0036658	.000284	.1421001	.1349064	.1492788

Note: There is a high autocorrelation after 500 lags.



b) Using prior from data provided (see do file for how variance was computed)

```
. bayesmh lwage educ exper smsa black south, likelihood(normal({var})) prior({lwage: _cons exper smsa black south}, flat) prior({lwage: educ},normal(0.06,1.97)) prior({var},
> jeffreys)
```

```
Burn-in ...
Simulation ...
```

Model summary

Likelihood:

```
lwage ~ normal(xb_lwage,{var})
```

Priors:

```
{lwage:_cons exper smsa black south} ~ 1 (flat) (1)
{lwage:educ} ~ normal(0.06,1.97) (1)
{var} ~ jeffreys
```

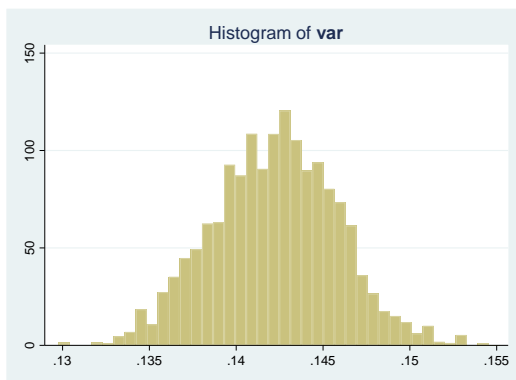
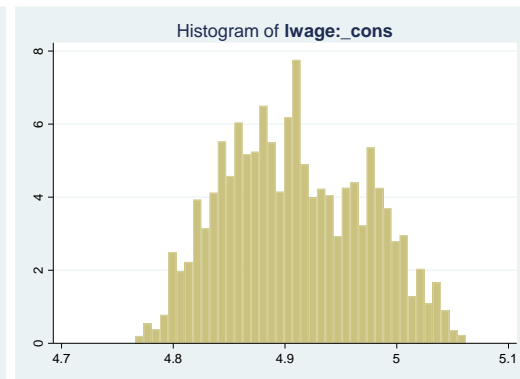
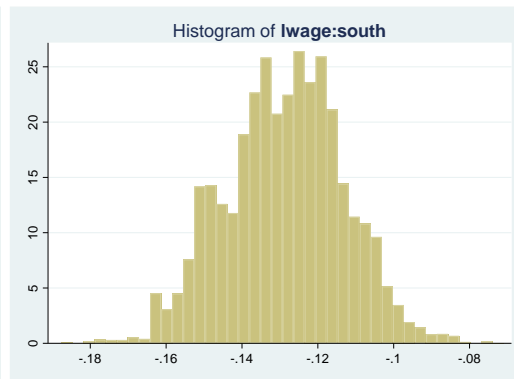
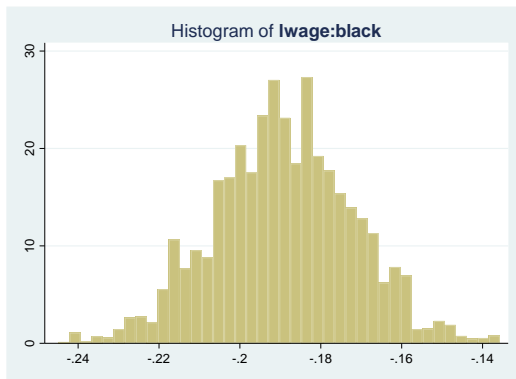
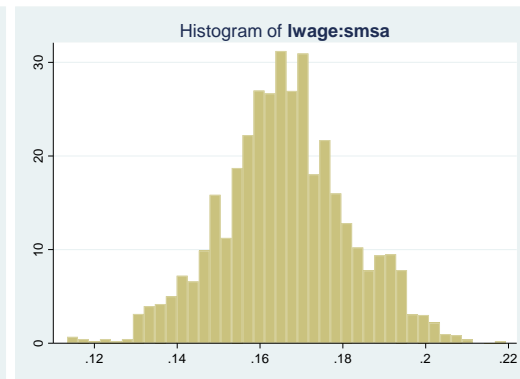
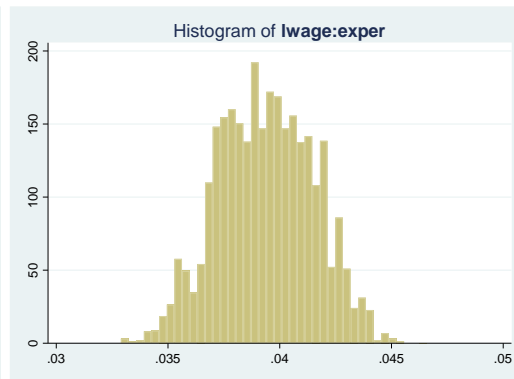
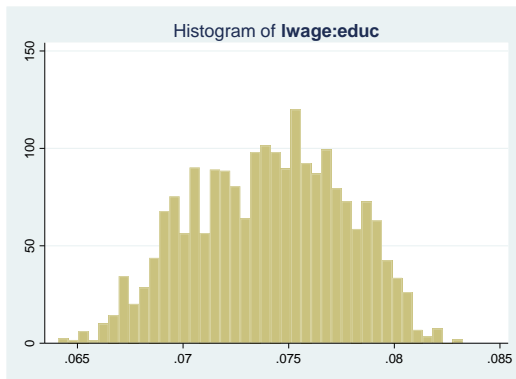
(1) Parameters are elements of the linear form xb_lwage.

```
Bayesian normal regression          MCMC iterations =    12,500
Random-walk Metropolis-Hastings sampling  Burn-in      =     2,500
                                         MCMC sample size =    10,000
                                         Number of obs   =     3,010
                                         Acceptance rate =     .1611
                                         Efficiency: min =    .001562
                                         avg =          .01878
                                         max =          .04299

Log marginal likelihood = -1361.7424
```

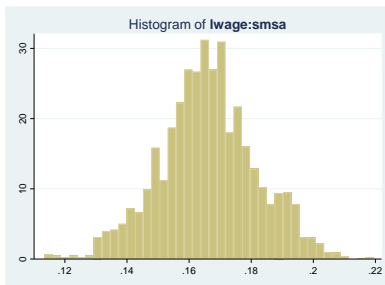
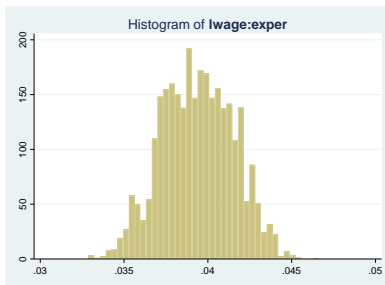
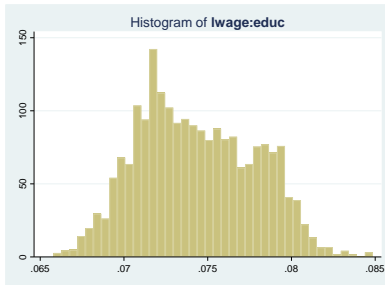
	Equal-tailed					
	Mean	Std. Dev.	MCSE	Median	[95% Cred. Interval]	
lwage						
educ	.0740197	.0035785	.00083	.074168	.0670933	.0803022
exper	.0393839	.0021328	.000468	.0393931	.0353249	.0433556
smsa	.166106	.0154831	.000816	.1658339	.1344929	.1964983
black	-.1891804	.017245	.001689	-.1893191	-.2233642	-.1556895
south	-.128783	.015629	.000754	-.1280511	-.1594032	-.0996628
_cons	4.908498	.0627174	.015867	4.904118	4.801841	5.029297
var	.1422329	.0036017	.000188	.1423463	.1351181	.1493051

Note: There is a high autocorrelation after 500 lags.

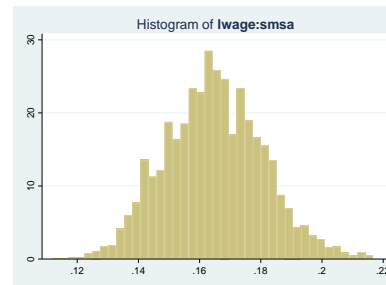
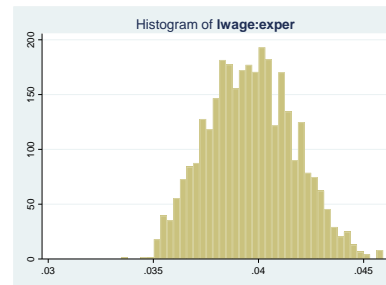
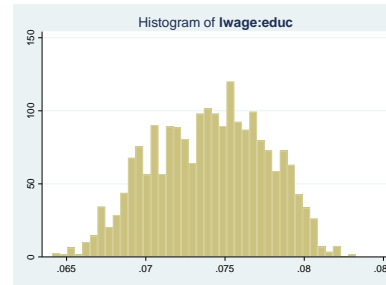


3) Doing a side-by-side comparison, prior distribution for education improved, centering around values closer to the mean. As a model, using prior from another study improved average efficiency (from 0.0054 to 0.01878) and at lower acceptance rate (from 0.239 to 0.161).

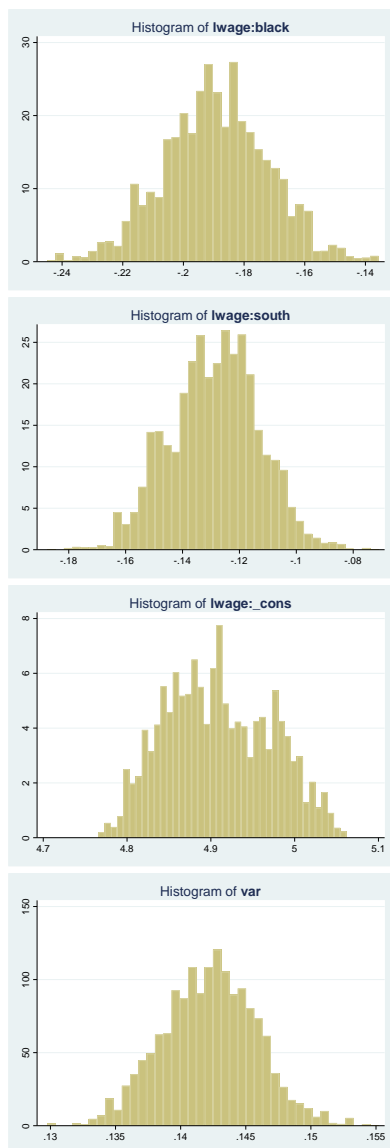
Flat prior for all



Using prior from another study



Flat prior for all



Using prior from another study

