

ONLINE APPENDIX to the article by Havranek, T., Herman, D., Irsova, Z.:
Does Daylight Saving Save Electricity? A Meta-Analysis

Table 9: Summary of BMA estimation: UIP

<i>Mean no. regressors</i>	<i>Draws</i>	<i>Burn-ins</i>	<i>Time</i>	<i>No. models visited</i>
6.0646	$2 \cdot 10^6$	$1 \cdot 10^6$	5.024066 mins	560,236
<i>Modelspace</i>	<i>Visited</i>	<i>Topmodels</i>	<i>Corr PMP</i>	<i>No. obs.</i>
16,384	34%	100%	1	162
<i>Model prior</i>	<i>g-prior</i>	<i>Shrinkage-stats</i>		
Uniform	UIP	$A_V = 0.9939$		

Notes: In this specification, we employ the priors suggested by Eicher *et al.* (2011), who recommend using the uniform model prior (each model has the same prior probability) and the unit information prior (the prior provides the same amount of information as one observation of the data).

Figure 9: Model size and convergence, BMA with UIP prior

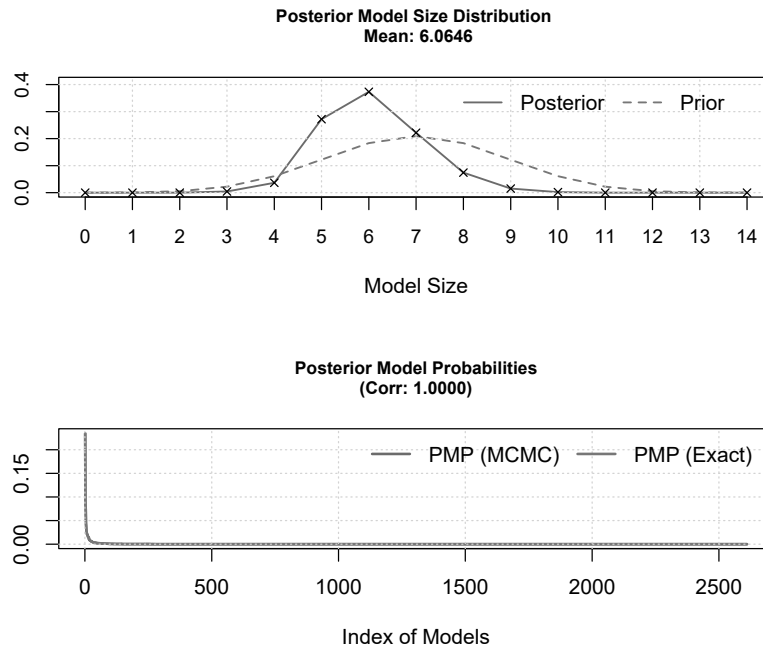
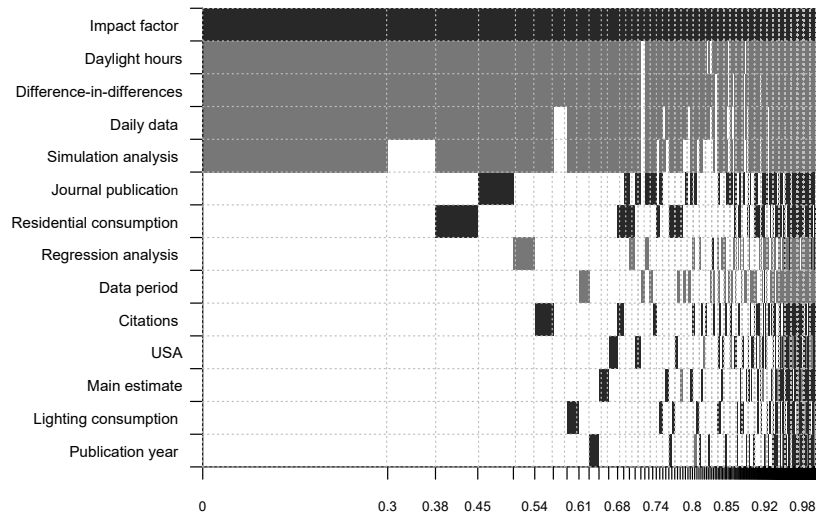
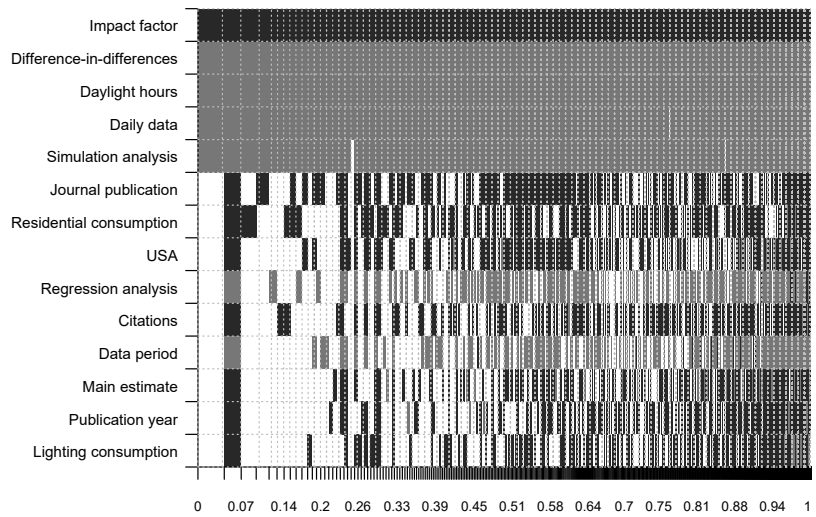


Figure 10: Model Inclusion in BMA with BRIC prior



Notes: Response variable: estimate of the DST effect in electricity savings. Columns denote individual models; variables are sorted by posterior inclusion probability in descending order. Darker color = the variable is included and the estimated sign is positive. Lighter color = the variable is included and the estimated sign is negative. No color = the variable is not included in the model. The horizontal axis measures cumulative posterior model probabilities. A detailed description of all variables is available in Table 4; numerical results of the BMA estimation are reported in Table 7.

Figure 11: Model Inclusion in BMA with hyper-g prior



Notes: Response variable: estimate of the DST effect in electricity savings. Columns denote individual models; variables are sorted by posterior inclusion probability in descending order. Darker color = the variable is included and the estimated sign is positive. Lighter color = the variable is included and the estimated sign is negative. No color = the variable is not included in the model. The horizontal axis measures cumulative posterior model probabilities. A detailed description of all variables is available in Table 4; numerical results of the BMA estimation are reported in Table 7.

Table 10: Summary of BMA estimation: BRIC

Mean no. regressors	Draws	Burn-ins	Time	No. models visited
5.5698	$2 \cdot 10^6$	$1 \cdot 10^6$	4.995537 mins	489,541
Modelspace	Visited	Topmodels	Corr PMP	No. obs.
16,384	29.88%	100%	1	162
Model prior	g-prior	Shrinkage-stats		
Random	BRIC	$A_v = 0.9949$		

Notes: The “random” model prior refers to the beta-binomial prior advocated by Ley and Steel (2009); Zellner’s g prior is set according to Fernandez *et al.* (2001).

Figure 12: Model size and convergence, BMA with BRIC prior

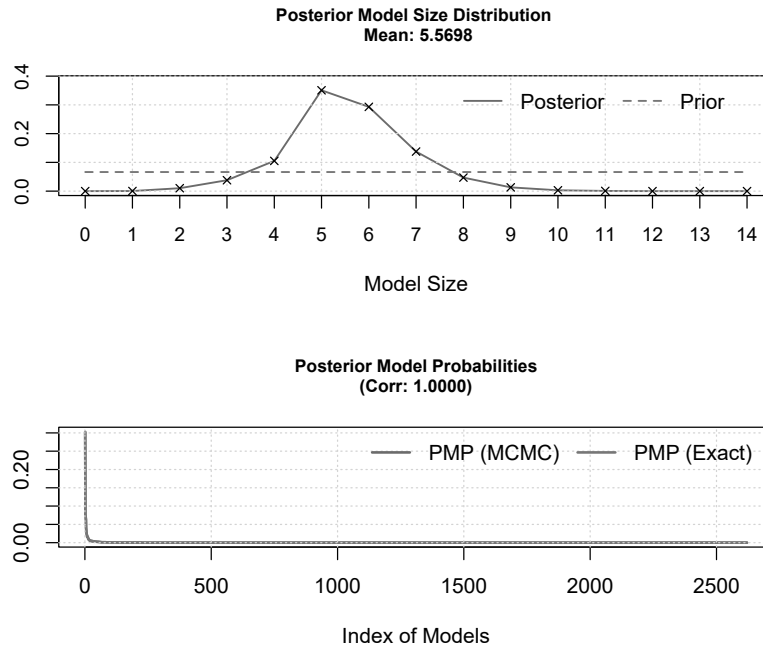


Table 11: Summary of BMA estimation: hyper-g

Mean no. regressors	Draws	Burn-ins	Time	No. models visited
8.7791	$2 \cdot 10^6$	$1 \cdot 10^6$	8.367627 mins	1,285,508
Modelspace	Visited	Topmodels	Corr PMP	No. obs.
16,384	78.46%	100%	0.9995	162
Model prior	g-prior			
Random	hyper (a=2.0102)	Shrinkage-stats Av = 0.9949, Stdev=0.042		

Notes: This specification of the “random” model uses the hyper-g prior suggested by Feldkircher and Zeugner (2012).

Figure 13: Model size and convergence, BMA with hyper-g prior

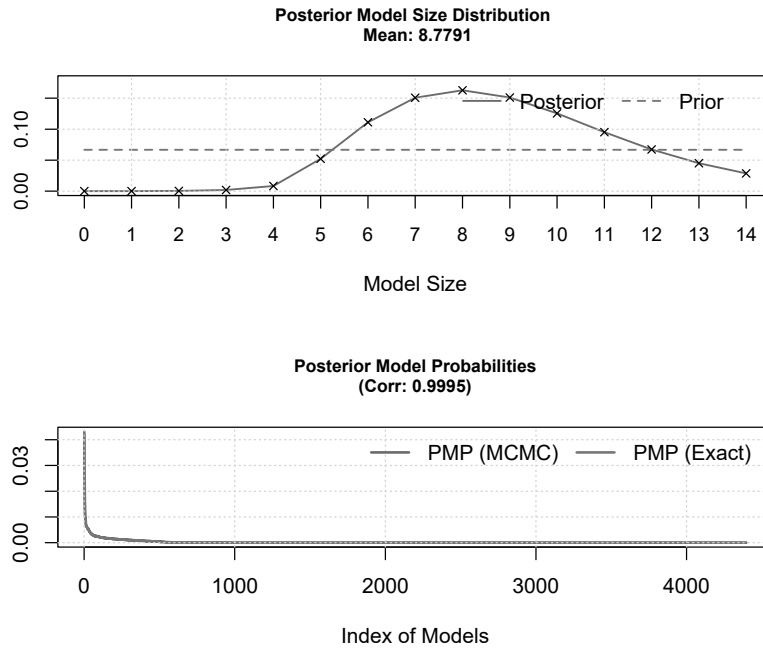
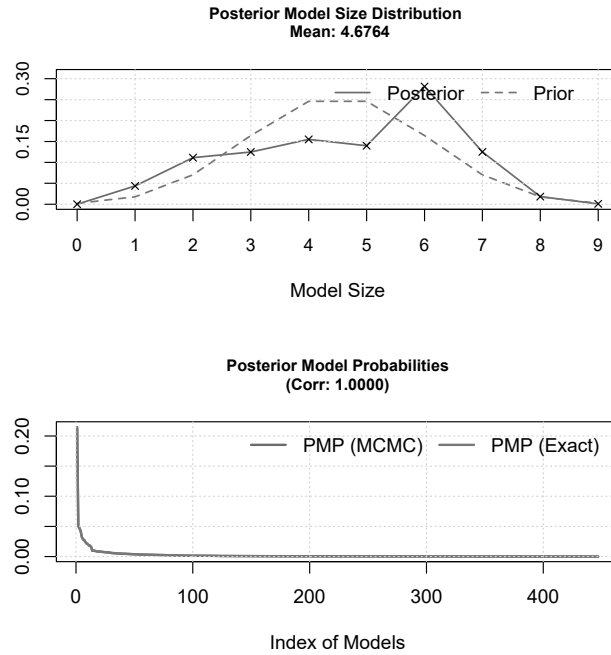


Table 12: Summary of BMA estimation: UIP, based on the US data

<i>Mean no. regressors</i>	<i>Draws</i>	<i>Burn-ins</i>	<i>Time</i>	<i>No. models visited</i>
4.6764	$2 \cdot 10^6$	$1 \cdot 10^6$	6.17748 mins	917,357
<i>Modelspace</i>	<i>Visited</i>	<i>Topmodels</i>	<i>Corr PMP</i>	<i>No. obs.</i>
512	19.62%	100%	1.0000	94
<i>Model prior</i>	<i>g-prior</i>	<i>Shrinkage-stats</i>		
Uniform	UIP	$A_V = 0.9895$		

Notes: In this specification, we employ the priors suggested by Eicher *et al.* (2011), who recommend using the uniform model prior (each model has the same prior probability) and the unit information prior (the prior provides the same amount of information as one observation of the data).

Figure 14: Model size and convergence: BMA with UIP prior, based on the US data



REFERENCES

- Eicher, T. S., C. Papageorgiou, and A. E. Raftery (2011). "Default priors and predictive performance in Bayesian model averaging, with application to growth determinants." *Journal of Applied Econometrics* 26(1): 30–55.
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