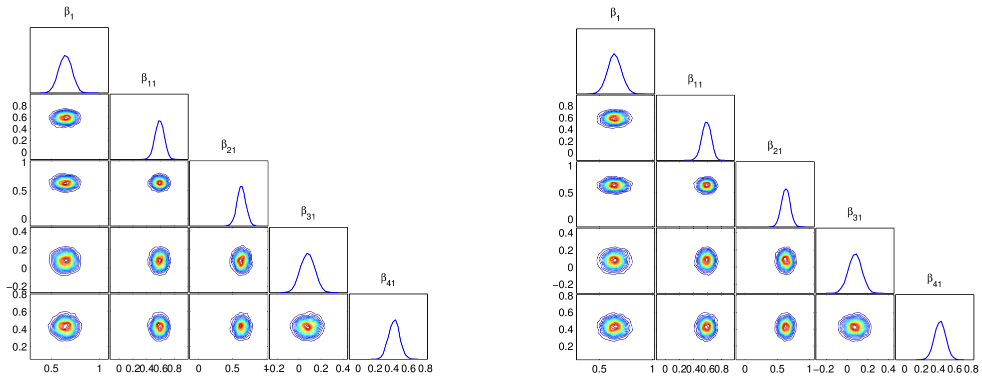

HMC　　　　RNS-HMC

Figure 6: HMC vs RNS-HMC: Comparing one- and two-dimensional posterior marginals of $\beta_1, \beta_{11}, \beta_{21}, \beta_{31}, \beta_{41}$ based on the logistic regression model with simulated data.

Experiment	Method	AP	ESS	s/Iter	$\min(\text{ESS})/\text{s}$	spdup
LR (Simulation)	HMC	0.76	(4351,5000,5000)	0.061	14.17	1
	RMHMC	0.80	(1182,1496,1655)	3.794	0.06	0.004
s = 2000	RNS-HMC	0.76	(4449,4999,5000)	0.007	123.56	**8.72**
	RNS-RMHMC	0.82	(1116,1471,1662)	0.103	2.17	0.15
LR (Bank Marketing)	HMC	0.70	(2005,2454,3368)	0.061	6.52	1
	RMHMC	0.92	(1769,2128,2428)	0.631	0.56	0.09
s = 1000	RNS-HMC	0.70	(1761,2358,3378)	0.007	52.22	**8.01**
	RNS-RMHMC	0.90	(1974,2254,2457)	0.027	14.41	2.21
LR (`a9a` 60 dimension)	HMC	0.72	(1996,2959,3564)	0.033	11.96	1
	RMHMC	0.82	(5000,5000,5000)	3.492	0.29	0.02
s = 2500	RNS-HMC	0.68	(1835,2650,3203)	0.005	81.80	**6.84**
	RNS-RMHMC	0.79	(4957,5000,5000)	0.370	2.68	0.22
Elliptic PDE	HMC	0.91	(4533,5000,5000)	0.775	1.17	1
	RMHMC	0.80	(5000,5000,5000)	4.388	0.23	0.20
s = 1000	RNS-HMC	0.75	(2306,3034,3516)	0.066	7.10	**6.07**
	RNS-RMHMC	0.66	(2126,4052,5000)	0.097	4.38	3.74

Table 1: Comparing the algorithms using logistic regression models and an elliptic PDE inverse problem. For each method, we provide the acceptance probability (AP), the CPU time (s) for each iteration and the time-normalized ESS.

`adult` dataset [46] which has been used to determine whether a person makes over 50K a year. We reduce the number of features to 60 by random projection (increasing the dimension to 100 results in a substantial drop in the acceptance probability). We set the step size and number of leapfrog steps $\epsilon = 0.012,\ L = 10$ for HMC and RNS-HMC; $\epsilon = 0.5,\ L = 4$ for RMHMC and RNS-RMHMC. All datasets are normalized to have zero mean and unit standard deviation. The priors are the same as before. The results for the two data sets are summarized in Table 1. As before, both RNS-HMC and RNS-RMHMC significantly outperform their counterpart algorithms.

5.2 Elliptic PDE inverse problem

Another computationally intensive model is the elliptic PDE inverse problem discussed in [42, 43]. This classical inverse problem involves inference of the diffusion coefficient in an elliptic PDE which is usually