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A comment on 'Mixed logit models: Accuracy and software choice.'

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The recent paper by Chang and Lusk (2011) contains a useful review of the facilities for estimating mixed logit models in three econometric software packages. The packages considered are SAS, NLOGIT-LIMDEP, and my *mixlogit* module for Stata (Hole, 2007). The review gives details of the different options and capabilities of the packages and also aims to evaluate their accuracy by using a Monte Carlo experiment. In this comment I provide evidence which suggests that the data generation process used in the paper by Chang and Lusk may produce datasets that do not contain sufficient variation to identify the parameters in the model empirically. This suggests that their experiment is not well-suited to evaluate the accuracy of the different mixed logit routines.

It has been demonstrated by Chiou and Walker (2007) that simulation methods can mask identification problems in the estimation of mixed logit models. This is particularly an issue when a small number of draws is used in the estimation process, although Chiou and Walker (2007) show that empirical unidentification can in some cases be masked at as many as 5000 pseudo-random draws and 2000 Halton draws. One sign of empirical unidentification is that the optimisation routine does not converge and/or parameter estimates 'explode'. Lack of convergence can therefore be an indication of an identification problem. In the following I will replicate the experiment conducted by Chang and Lusk (2011) with the aim of further examining the cases where the Stata *mixlogit* routine does not converge.[1]

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[1] The Stata code that I used to replicate the experiment is available on request.

I generated 500 datasets with size $N = 200$ following section 4.1 in Chang and Lusk (2011) using Stata 11. The *mixlogit* routine declared non-convergence with one of these datasets which was chosen for further examination. With this dataset I re-estimated the mixed logit model using three alternative packages: NLOGIT 4, Biogeme 1.8 (Bierlaire, 2003) and Matlab 7, using the Matlab routine written by Kenneth Train (http://elsa.berkeley.edu/~train/software.html).[2] The models were run using 50, 500 and 5000 Halton draws to evaluate the simulated log-likelihood function. In all the runs multinomial logit estimates were used as starting values for the means and the starting values for the standard deviations were set to 0.1.[3]

Table 1. Mixed logit estimation results. 50 Halton draws.

		NLOGIT		Biogeme		Matlab	
Parameter	True value	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
β_1	2	3.95	1.30	3.34	1.06	3.91	1.27
σ_1	1	1.63	0.95	1.32	0.87	1.59	0.94
β_2	5	10.81	3.71	8.68	2.84	10.69	3.67
σ_2	1	3.66	1.64	2.15	1.50	3.61	1.63
Number of obs.		200		200		200	
Simulated LL		-50.97		-51.75		-51.18	

In the runs using 50 Halton draws (Table 1) all the packages declare convergence and produce reasonable-looking results. When increasing the number of draws to 500, however, the packages show signs of the model being unidentified: NLOGIT displays a warning message saying that the 'log likelihood is flat at the current estimates', Biogeme does not declare convergence after 1000 iterations (the default maximum) and the Matlab results show signs of 'exploding' parameters.[4] Further increasing the number of draws to 5000 gives similar results, and in this case Biogeme issues a

[2]The Stata, NLOGIT and Biogeme analysis was carried out on a PC with an Intel Core 2 Duo CPU processor, 3.00 GHz, with 3.23 GB of RAM running Microsoft Windows XP Professional Version 2002 (Service Pack 3). The Matlab analysis was carried out on Iceberg, the University of Sheffield's high performance computing server, see http://www.sheffield.ac.uk/wrgrid/iceberg for detailed specifications.

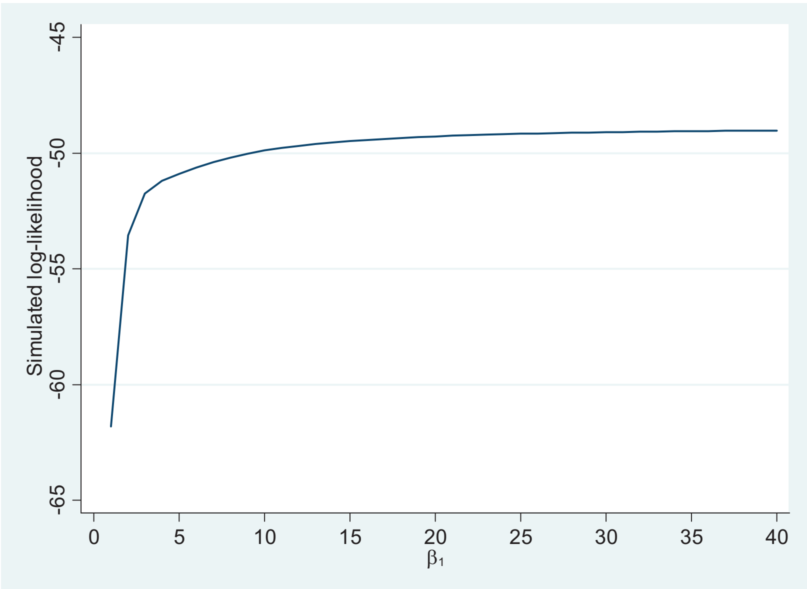
[3]When using alternative starting values Biogeme sometimes converged to different solutions but the value of the simulated log-likelihood at convergence for these runs was lower than for the results presented here.

[4]The coefficient estimates at convergence are 52364.07 (β_1), 24081.74 (σ_1), 159525.68 (β_2) and 66120.58 (σ_2).

warning that the model is 'unidentifiable'. Taken together these findings suggest that the model is empirically unidentified using the criteria proposed by Chiou and Walker (2007).

As further evidence of this conclusion Figure 1 plots the maximum of the simulated log-likelihood function over a range of values for β_1.[5] It is clear from the figure that the likelihood function is virtually flat over a wide range of β_1 values, which again suggests that the model is empirically unidentified.

Figure 1. Plot of the maximum of the simulated log-likelihood function over a range of values for β_1



The findings presented in this note suggest that the data generation process used in Chang and Lusk (2011) is not well-suited to evaluate the accuracy of the software packages considered in the review, as at least in some cases the generated dataset does not contain enough variation to identify the parameters in the model. While the authors' conclusions regarding the options and capabilities of the various mixed logit routines are uncontroversial, further research is needed to determine which software package is the most accurate.

[5]The figure was generated in Stata 11 using the *mixlogit* module with 500 Halton draws to obtain the simulated log-likelihood values.

References

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