Hybrid Choice Models and accounting for the endogeneity of indicator variables: a Monte Carlo investigation

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- ► Why Hybrid Choice Models?
 - ► Allow for inclusion of 'soft' variables such as perceptions and attitudes into the choice model using latent variables framework
 - Direct incorporation of indicator variables into choice model may lead to biased estimates due to endogeneity and measurement problems
 - ► "To what extent do you agree with the statement that the results of the survey will influence future policy?" (from 1 - 'definitely disagree' to 5 - 'definitely agree')
 - More 'behavioral' approach for explaining heterogeneity

- ► Hybrid Choice models (HCM) usually consist of three parts:
 - ► Choice equations (utility):

$$V_{ijt} = \mathbf{\beta}_i' \mathbf{X}_{ijt} + e_{ijt}$$

$$\boldsymbol{\beta}_i = \boldsymbol{\Lambda} \mathbf{L} \mathbf{V}_i + \boldsymbol{\Omega} \mathbf{S} \mathbf{D}_i + \boldsymbol{\beta}_i^*$$

Structural equations:

$$\mathbf{L}\mathbf{V}_{i} = \mathbf{\Psi}'\mathbf{X}_{i}^{str} + \mathbf{\xi}_{i}$$

► Measurement equations

$$\mathbf{I}_{i} = \mathbf{\Gamma} \mathbf{L} \mathbf{V}_{i} + \mathbf{\Phi} \mathbf{X}_{i}^{Mea} + \mathbf{\eta}_{i}$$

- ► Reasons for endogeneity (Chorus and Kroesen, 2014):
 - missing variables which influence both latent variable and choices of individuals
 - learning effects
 - ▶ individuals tend to align their attitudes with their actual choices in order to seem consistent
- ▶ Daly et al. (2011) states: "The advantages of the latent variable framework over deterministic attitude incorporation are clear; the model is not affected by endogeneity bias [...]"
- ► Similar statements in Hess and Stathopoulos (2013), Hess, Shires and Jopson (2013), Kløjgaard and Hess (2014) and Bello and Abdulai (2015)

- ► Two types of indicator variables endogeneity:
 - ▶ LV-endogeneity
 - ► Latent variable is endogenous in itself
 - ► Correlated error terms in choice model and structural equations
 - ► ME-endogeneity
 - ▶ Indicator variables are endogenous, but latent variable is not
 - ► Correlated error terms in choice model and measurement equations
- Simulation with 1'000 individuals, 6 choice tasks per person, 3 alternatives per choice task (including the Status Quo)
- ▶ 100 repetitions

► Data generating process:

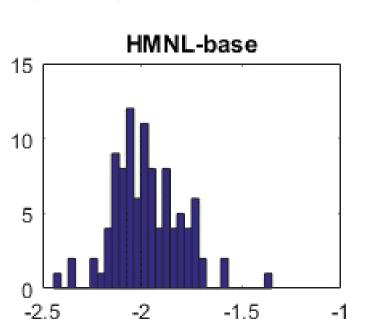
	LV-endogeneity	ME-endogeneity		
Utility function	$V_{ijt} = \beta_{1i}SQ_{ijt} + \beta_{2i}Quality_{ijt} + \beta_{3i}Cost_{ijt} + e_{ijt}$ $\beta_{1i} = -4 - 2LV_i^{norm} - 2X_i^{Miss}$ $\beta_{2i} = 5 + 2LV_i^{norm}$ $\beta_{3i} = -3 + 1LV_i^{norm}$	$V_{ijt} = \beta_{1i}SQ_{ijt} + \beta_{2i}Quality_{ijt} + \beta_{3i}Cost_{ijt} + e_{ijt}$ $\beta_{1i} = -4 - 2LV_i^{norm} - 2X_i^{Miss}$ $\beta_{2i} = 5 + 2LV_i^{norm}$ $\beta_{3i} = -3 + 1LV_i^{norm}$		
Structural equations	$LV_i = -2X_i^{SD} + 1X_i^{Miss} + \xi_i$	$LV_i = -2X_i^{SD} + \xi_i$		
Measurement equations	$I_{i1} = -1 + 1LV_i^{norm} + 0.5\eta_{i1}$ $I_{i2} = 1 - 1LV_i^{norm} + 0.5\eta_{i2}$	$I_{i1} = -1 + 1LV_i^{norm} + 1.5X_i^{Miss} + 0.5\eta_{i1}$ $I_{i2} = 1 - 1LV_i^{norm} - 0.5X_i^{Miss} + 0.5\eta_{i2}$		

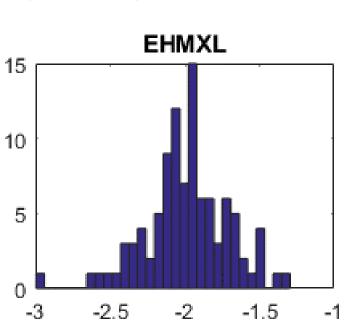
HCM Literature Simulation Results Conclusions

Estimated models:

HMNL- base	The same specification as in DGP	No missing variables
MNL- base	Including indicator variables directly into the choice model	No missing variables
HMNL	The same specification as in DGP	$X_i^{ extit{Miss}}$ is missing
HMXL	The same specification as in DGP + random parameter for SQ	X_i^{Miss} is missing
EHMXL	The same specification as in DGP + random parameter for SQ + correlation between random parameter and \mathcal{E}_i	$X_i^{ extit{Miss}}$ is missing
HMNL2	The same specification as in DGP + second LV in both measurement equations	$X_i^{ extit{Miss}}$ is missing
MXL	Including indicator variables directly into the choice model + random parameter for SQ	$X_i^{ extit{Miss}}$ is missing

	value						
				Utility function			
SQ	-4	-3.9949*	-2.9439	-3.4352*	-4.0072*	-3.9974*	-4.0674*
	-4	[-4.5009 -3.6244]	[-3.2650 -2.6970]	[-4.0052 -2.9512]	[-4.5648 -3.4461]	[-4.6198 -3.4770]	[-4.6970 -3.5655]
Quality	5	5.0086*	4.4587	4.8979*	4.9892*	4.9990*	4.7 <mark>59</mark> 3*
Quanty	3	[4.7234 5.3378]	[4.2042 4.7083]	[4.6343 5.2492]	[4.7224 5.3371]	[4.7320 5.3502]	[4.5070 <mark>5.0</mark> 488]
Cost	-3	-3.0028*	-2.661	-2.8864*	-3.0001*	-3.0003*	-2.89 <mark>45*</mark>
Cost	-3	[-3.2166 -2.8111]	[-2.8241 -2.4999]	[-3.0828 -2.7077]	[-3.1969 -2.8215]	[-3.2093 -2.8171]	[-3.0963 -2 <mark>.7162</mark>]
SQ x Miss	-2	-2.0183*	-1.7025*	_	2.2335*	2.0182*	2.6393
(or RP)	2	[-2.4011 -1.7051]	[-2.0087 -1.3931]		[1.8243 2.6402]	[1.5191 2.4058]	[2.3189 2.9859]
SQ x LV	2	-1.9716*	-0.606	-2.5318	-2.7113	-1.9840*	-1.3291
(or I_1)	-2	[-2.3439 -1.5921]	[-0.8884 -0.3111]	[-3.0434 -2.0386]	[-3.2260 -2.1443]	[-2.5466 -1.4656]	[-1.8569 -0.8997]
Quality x	2	2.0108*	0.8114	2.1267*	1.9849*	2.0038*	0.803
LV (or I_1)	2	[1.7407 2.3351]	[0.5385 1.0257]	[1.8867 2.4722]	[1.7443 2.3580]	[1.7651 2.3573]	[0.5394 1.0548]
Cost x LV		1.0031*	0.3549	0.8707*	1.0053*	1.0021*	0.4351
(or I_1)	1	[0.8201 1.2025]	[0.1610 0.5847]	[0.7097 1.0437]	[0.8192 1.1917]	[0.8083 1.1980]	[0.2278 0.6603]
I			0.6212				1.3251
$\mathbf{SQ} \times I_2$		-	[0.3426 1.0147]	-	-	-	[0.8985 1.8941]
Quality x			-0.7745				-0.7731
I_2		-	[-1.0423 -0.4355]	-	-	- /	[-1.0654 -0.4604]
σ . I		-	-0.3424	-	-		-0.4228
Cost x I_2			[-0.5750 -0.1700]				[-0.6611 -0.1959]





	НСМ		Literature	Simulation		Results		Conclusions	
Variable	True value	HMNL-base	MNL-base	HMNL	HMXL	EHMXL	HMNL2	MXL	
	Utility function								
SQ	-4	-3.9906*	-2.9831	-3.9218*	-3.9421*	-3.9350*	-4.0098*	-4.0823*	
~ €		[-4.4414 -3.480	[-3.3499 -2.6748]	[-4.4117 -3.4665]	[-4.4120 -3.4749]	[-4.3918 -3.4995]	[-4.5693 -3.5050	[-4.5824 - <mark>3.6172</mark>]	
Quality	5	5.0169*	4.4738	4.7127	4.7135	4.6508	5.0107*	4.4063	
		[4.6879 5.277]	1] [4.2009 4.7062]	[4.4286 4.9429]	[4.4325 4.9391]	[4.3286 4.8903]	[4.6596 5.312 <mark>2</mark>]	[4.1470 4.6497]	
Cost	-3	-3.0031*	-2.6774	-2.8775*	-2.8799*	-2.8536*	-3.0036*	-2.7533	
SO v Migg		[-3.2032 -2.816		[-3.0397 -2.7008]	[-3.0383 -2.7010]	[-3.0257 -2.6736]	[-3.1903 -2.7977		
SQ x Miss (or	-2	-2.0090*	-0.3265	-	0.8616	0.9866	-2.1307*	1.9289*	
RP/LV2)		[-2.3235 -1.749	[-0.7444 0.0572]		[0.4942 1.7094]	[0.4703 1.6758]	[-2.4328 -1.7481	[1.6231 2.2177]	
SQ x LV	-2	-2.0031*	-0.6528	-2.578	-2.5824	-2.9621	-1.9657*	-1.0035	
$($ or $I_1)$		[-2.4012 -1.548	[-0.9526 -0.3617]	[-3.0498 -2.0381]	[-3.0499 -2.0591]	[-3.5008 -2.3941]	[-2.4395 -1.5098	[-1.2234 -0.8042]	
Quality x	2	2.0058*	0.8301	1.717	1.7105	1.6407	1.9972*	-0.2308	
LV (or I_1)) _	[1.6895 2.2645	[0.5990 1.1070]	[1.4181 1.9407]	[1.4175 1.9421]	[1.3262 1.9075]	[1.6629 2.2 <mark>792</mark>]	[-0.3739 -0.0608]	
Cost x LV	1	0.9839*	0.3443	0.8438*	0.8468*	0.8228	0.9826 <mark>*</mark>	-0.0916	
(or I_1)	1	[0.8243 1.167]	[0.1787 0.5617]	[0.6379 1.0020]	[0.6394 1.0105]	[0.6216 0.9822]	[0.7997 1.1662]	[-0.2074 0.0193]	
so I			0.6457					1.019	
$\mathbf{SQ} \times \mathbf{I}_2$		-	[0.2516 0.9509]	-	-	-		[0.6110 1.4040]	
Quality x			-0.8143					-1.2968	
I_2		-	[-1.0563 -0.5328]	-	-	-		[-1.5695 -0.9740]	
7			-0.3444					-0.6996	
Cost x I_2		-	[-0.5482 -0.0897]	-	-	/ -		[-0.8788 -0.5243]	

- Currently used Hybrid Choice models do not account for the endogeneity of indicator variables
- Measurement bias can be substantial
 - ► Even with continuous indicator variables
 - ▶ In some instances endogeneity bias can correct measurement bias
- Possible solutions
 - ▶ Allowing for correlation between error terms in structural equations and choice model may help
 - ► Additional Latent Variables to capture residual correlation
 - ► Identification may be impossible, particularly with the two-step estimation procedure