ENDOGENEITY OF INDICATOR VARIABLES IN HYBRID CHOICE MODELS:

MONTE CARLO INVESTIGATION VS. STATED PREFERENCE STUDY

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Outline

- Budzinski and Czajkowski (2020). *Endogeneity and measurement bias of the indicator variables in hybrid choice models: A Monte Carlo investigation*
  - Introduction to hybrid choice models
  - Endogeneity and hybrid choice models
  - Monte Carlo simulation setup
  - Monte Carlo simulation results
- Budzinski, Czajkowski and Zawojska (2020). *Endogeneity of self-reported consequentiality in stated preference studies*
  - Stated preferences and consequentiality
  - Data
  - Results

Hybrid choice models

- Initially proposed by Ben-Akiva et al. (1999) and Ben-Akiva et al. (2002)
- General framework for more complex choice models
  - Flexible disturbances
  - Explicit modelling of latent psychological factors
  - Latent segmentation for different decision protocols
- Integrated Choice and Latent Variables models focus mostly on the second point
  - Although currently the names are used interchangeably
- Useful when we are interested in the effect of ‘soft’ (not objectively measureable) variables, such as perceptions and attitudes, on choices / preferences
  - More ‘behavioral’ approach for explaining preference heterogeneity

Hybrid choice models

Discrete choice model
(e.g. mixed logit model)

Latent variables influence preferences

$$U_{ijt} = \boldsymbol{\beta}_i' \boldsymbol{X}_{ijt} + e_{ijt}$$

$$\boldsymbol{\beta}_i = \boldsymbol{\Lambda}\mathbf{LV}_i + \boldsymbol{\Omega}\mathbf{SD}_i + \boldsymbol{\beta}_i^*$$

$$\mathbf{LV}_i = \boldsymbol{\Psi}'\mathbf{X}_i^{str} + \boldsymbol{\xi}_i$$

Latent variables
(structural equation)

Unobserved psychological factors

$$\mathbf{I}_i = \boldsymbol{\Gamma}\mathbf{LV}_i + \boldsymbol{\Phi}\mathbf{X}_i^{Mea} + \boldsymbol{\eta}_i$$

Measurement equations

Latent variables influence indicators
(e.g. "*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')

Hybrid choice models

- Alternative approach is to directly include indicator variables into a choice model
  - Does not require a more complex choice model
- This approach is usually considered to be methodologically flawed
  - Indicators are not direct measures of latent constructs but rather their functions – <u>measurement bias</u>
  - There may be unobserved effects that influence both a respondent's choice and their responses to indicator questions – <u>endogeneity bias</u>
- The use of HCMs is usually motivated by the claims that they solve those issues
- <u>We investigate whether that is really the case with Monte Carlo simulations</u>

Endogeneity and hybrid choice models

- Measurement error causes endogeneity in and by itself (Walker et al. 2010)
  - We treat it as a separate issue
- Chorus and Kroesen (2014) list possible reasons for endogeneity of latent variables:
  - 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
- Hybrid choice models have been used to solve endogeneity issue caused by some observed covariates
  - For example, effect of price when quality is unobserved
  - HCM can be used to impute missing variable
  - We do not study this. In our case indicators are the cause of endogeneity, rather than the solution for it

Endogeneity and hybrid choice models

- We consider two types of indicator variables' endogeneity:
  - LV-endogeneity
    - Latent variable is endogenous in itself
    - Correlated error terms in choice model and structural equations
  - M-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)
- 1000 repetitions

Simulation setup

- DGP:

Missing variable enters utility only through interaction with ASC

Endogeneity is caused by missing variable

	LV-endogeneity	**M-end**
Utility function	$V_{ijt} = \beta_{1i} SQ_{ijt} + \beta_{2i} Quality_{ijt} + \beta_{3i} Cost_{ijt} + e_{ijt}$ $\beta_{1i} = \alpha_{11} + \alpha_{12} LV_i + \alpha_{13} X_i^{Miss}$ $\beta_{2i} = \alpha_{21} + \alpha_{22} LV_i$ $\beta_{3i} = \alpha_{31} + \alpha_{32} LV_i$	
Indicator variables (measurement component)	$I_{i1} = \alpha_{41} + \alpha_{42} LV_i + \alpha_{43} \eta_{i1}$ $I_{i2} = \alpha_{51} + \alpha_{52} LV_i + \alpha_{53} \eta_{i2}$	$I_{i1} = \alpha_{41} + \alpha_{42} LV_i + \alpha_{43} \eta_{i1} + \alpha_{44} X_i^{Miss}$ $I_{i2} = \alpha_{51} + \alpha_{52} LV_i + \alpha_{53} \eta_{i2} + \alpha_{54} X_i^{Miss}$
Latent variables (structural component)	$LV_i^* = \alpha_{61} X_i^{SD} + \xi_i + \alpha_{62} X_i^{Miss}$	$LV_i^* = \alpha_{61} X_i^{SD} + \xi_i$

Simulation setup

- Estimated models:
  - Base models allow us to check whether simulation works properly, and the extent of a measurement bias:

	Model type	**Measurement error**	**Endogeneity**	**Description**
Model 1	Hybrid MNL	No	No	No missing variables
Model 2	MNL	Yes	No	No missing variables, indicator variables entering directly

Simulation setup

- Next we analyze the extent of error arising due to:
  - Endogeneity and measurement bias jointly
  - Endogeneity bias and ignoring the preference heterogeneity
  - Endogeneity bias

	Model type	Measurement error	Endogeneity	Description
Model 3	MXL	Yes	Yes	missing variable, random ASC indicator variables entering directly
Model 4	Hybrid MNL	Controlled	Yes	missing variable
Model 5	Hybrid MXL	Controlled	Yes	missing variable, random ASC

- These are models which are most likely to be used by researchers

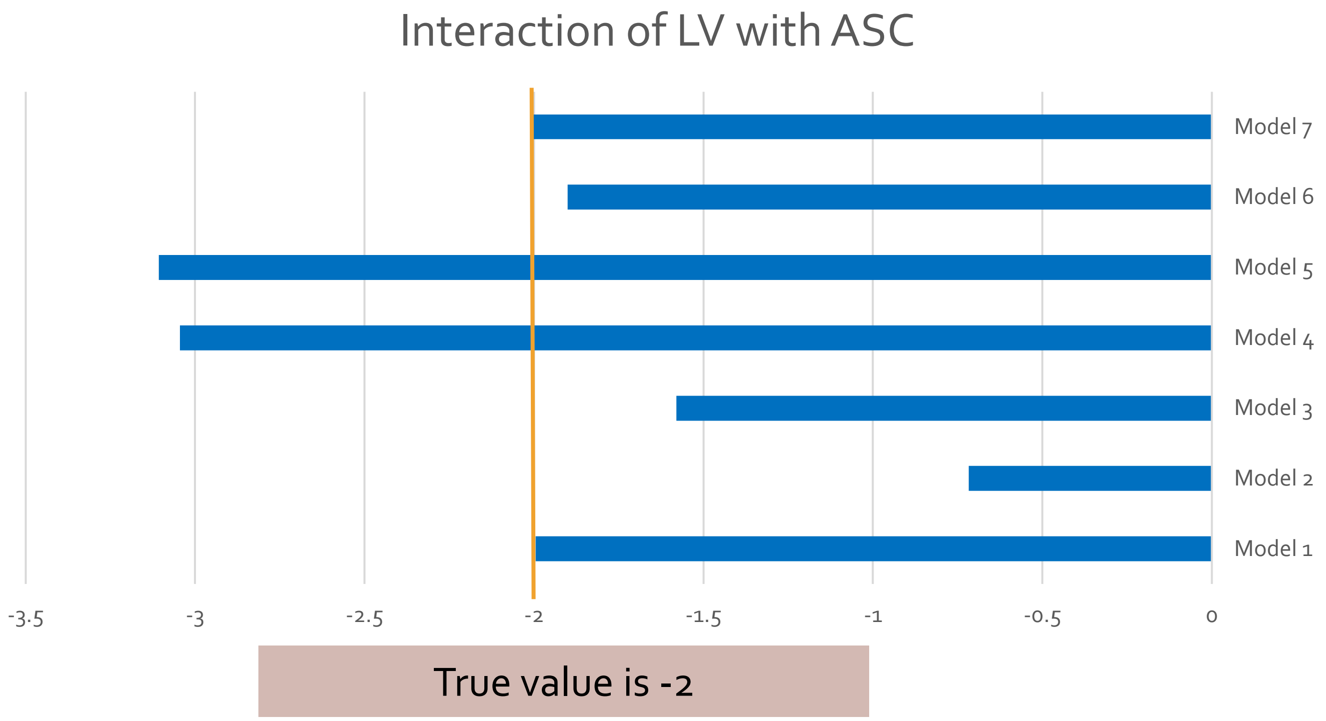
Simulation setup

- Lastly, we propose two different methods to mitigate endogeneity bias:
  - Directly modeling the correlation between latent factor and random parameters
  - Incorporating additional latent variable to account for residual correlation between error terms

	Model type	Measurement error	Endogeneity	Description
Model 6	Hybrid MXL	Controlled	Controlled	missing variable, random ASC, additional correlation
Model 7	Hybrid MNL	Controlled	Controlled	missing variable, additional LV in model specification

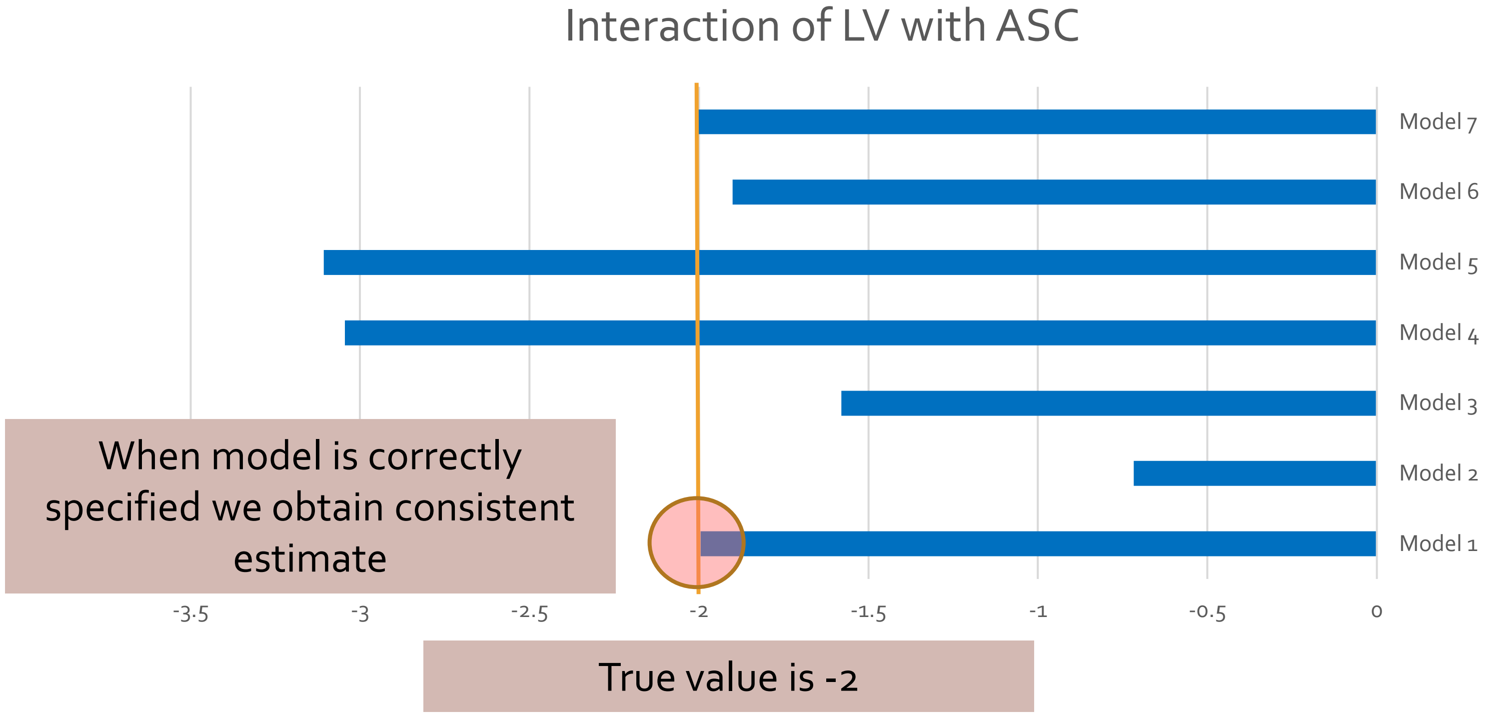
Simulation results

- LV - endogeneity



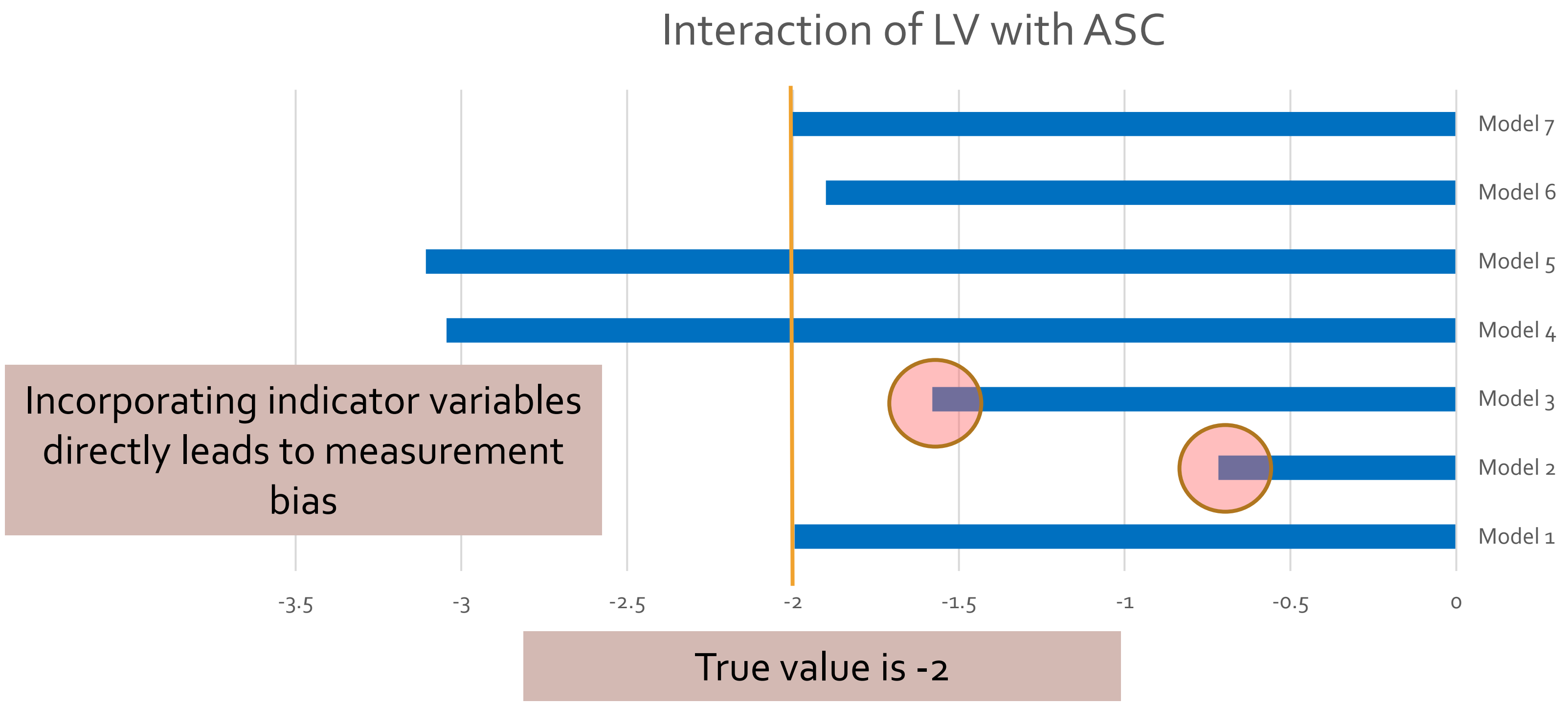
Simulation results

- LV - endogeneity



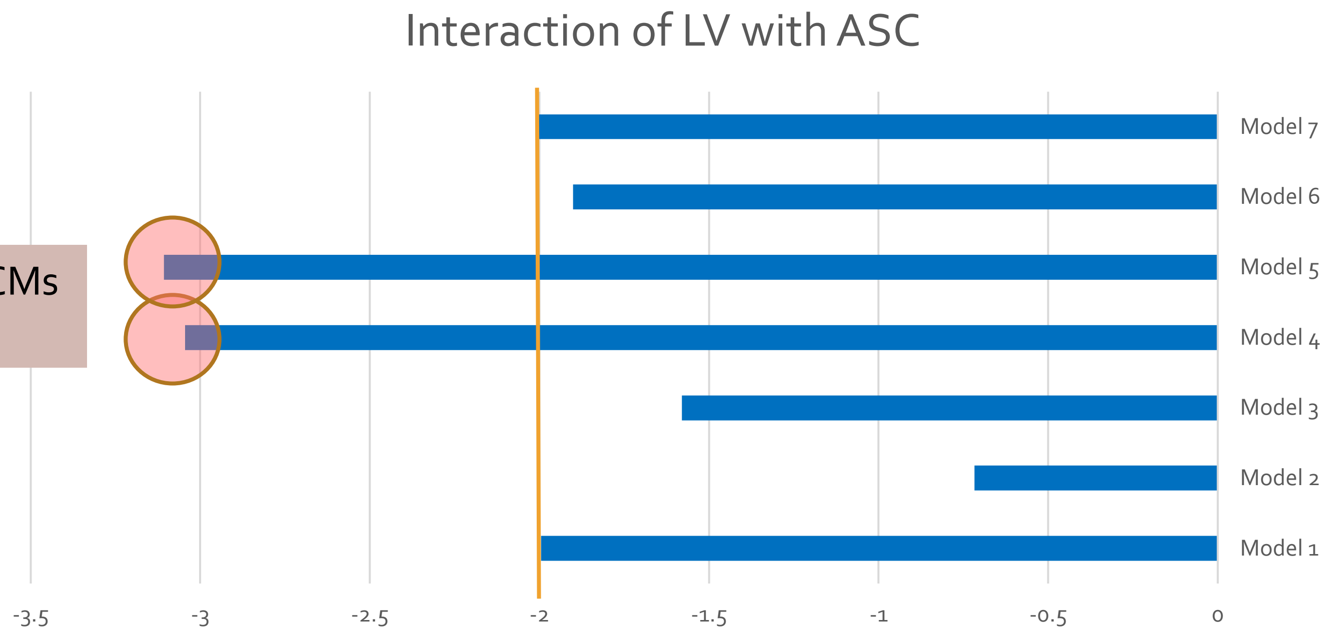
Simulation results

- LV - endogeneity



Simulation results

- LV - endogeneity

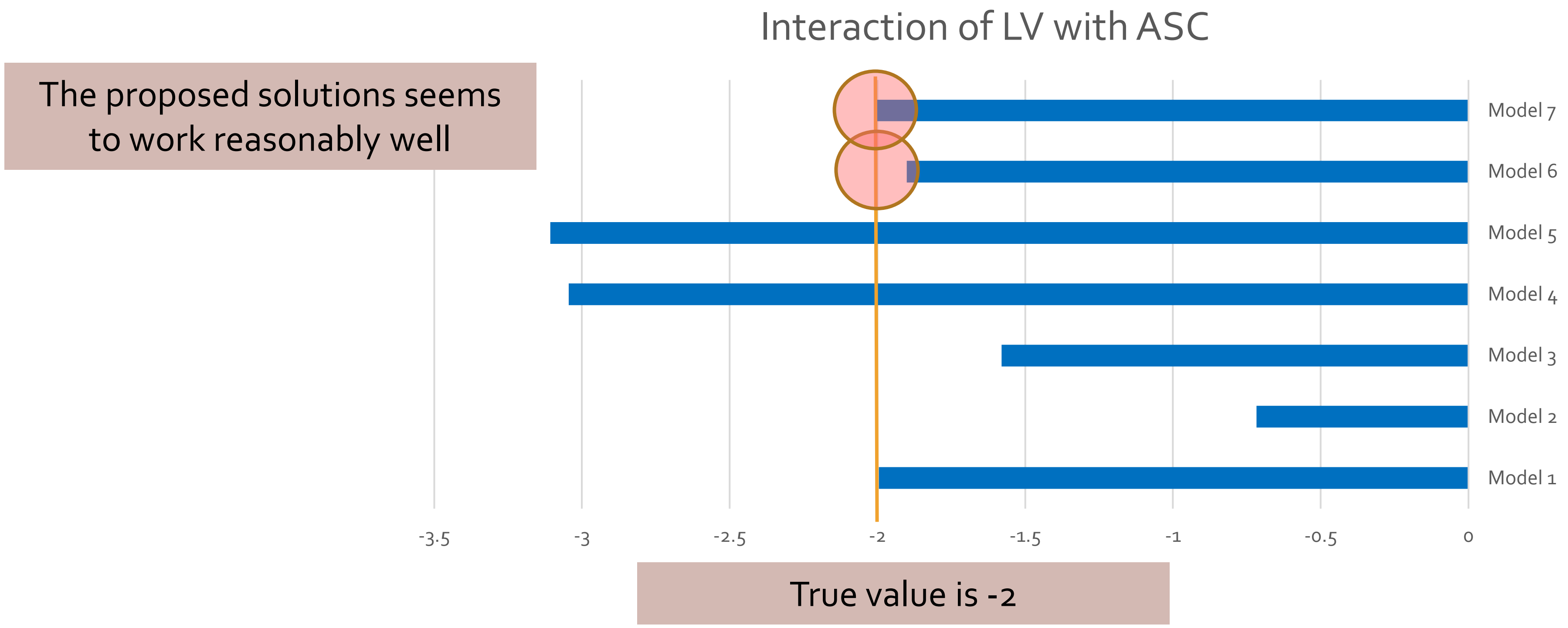


Standard specification of HCMs also does not work

True value is -2

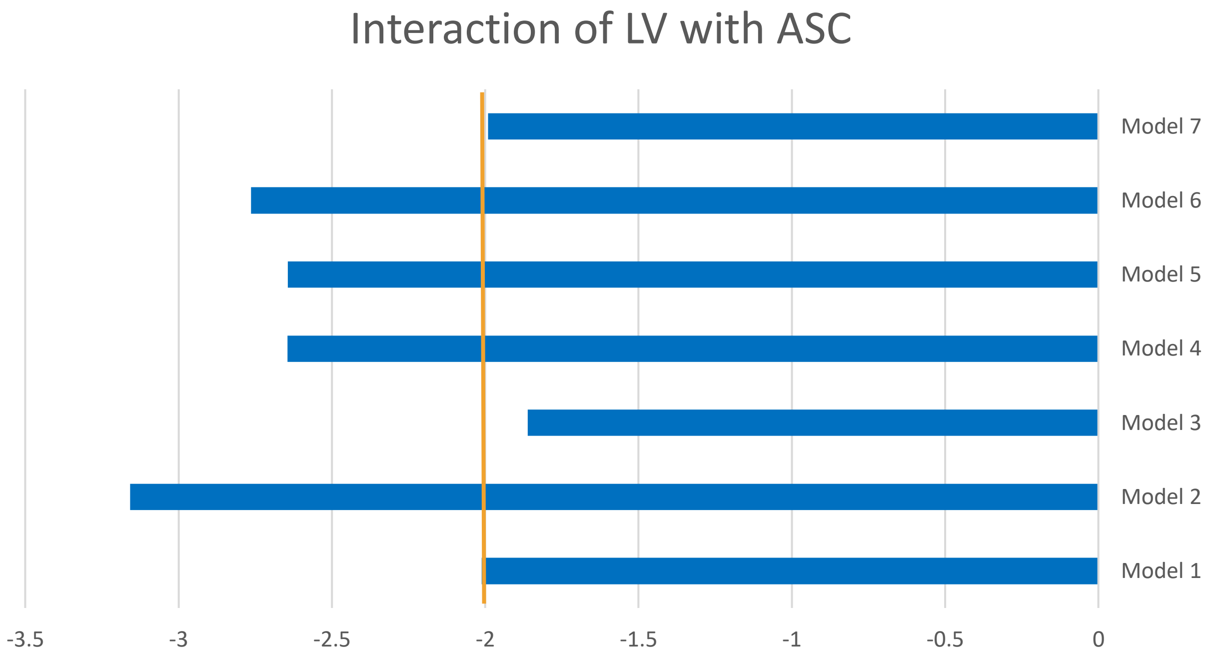
Simulation results

- LV - endogeneity



Simulation results

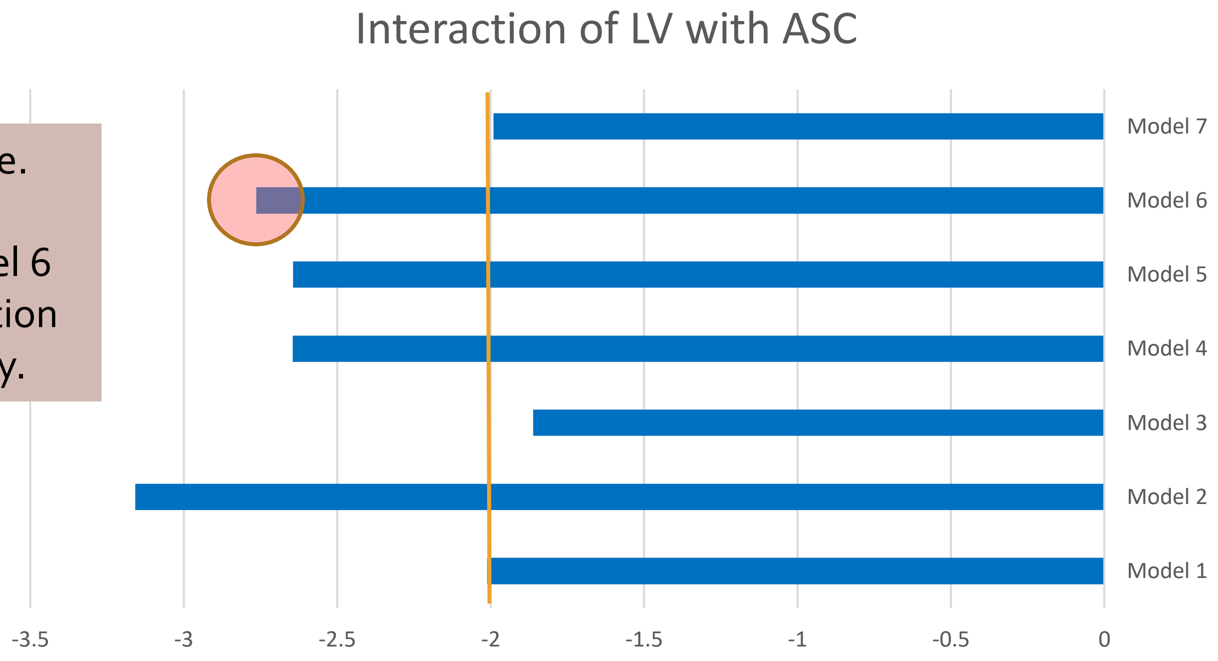
- M - endogeneity



True value is -2

Simulation results

- M - endogeneity



General conclusions are the same.

The main difference is that Model 6 leads to biased results. This solution does not work for M-endogeneity.

True value is -2

Simulation results

- M – endogeneity seems to affect more coefficients than LV-endogeneity
  - Parameters in structural and measurement components are also biased
  - In LV-endogeneity case bias in structural component is also possible
- As expected in LV-endogeneity case Models 6 and 7 have similar log-likelihood value
  - In M-endogeneity case Model 7 has much better fit

Simulation results - summary

- Usually used specifications of HCMs do not account for the endogeneity of indicator variables
- Measurement bias can be substantial
  - Even with continuous indicator variables
- 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
    - The former does not work with M-endogeneity

Endogeneity of Self-Reported Consequentiality in Stated Preference Studies

Wiktor Budziński, Mikołaj Czajkowski, Ewa Zawojska

Stated preference methods

- Widely used to measure the value of non-market goods, especially public goods
- In transportation, marketing, health, culture, environmental economics, …
- Based on surveys
- Many advantages:
  - Capture use and passive-use values
  - Go beyond the scope of the existing data
- But also important disadvantages:
  - Not based on market behavior
  - Might be viewed as not related to direct consequences
  - Incentive properties insufficiently understood

Conditions for truthful preference disclosure
(Carson and Groves 2007; Carson et al. 2014; Vossler et al. 2012)

One of the conditions requires the survey consequentiality

A necessary condition for truthful preference disclosure:

Consequentiality

- "a survey's results are seen by the agent as <u>potentially influencing</u> an agency's actions and the agent cares about the outcomes of those actions"
  (Carson and Groves 2007)
- "an individual faces or perceives a nonzero probability that their responses will <u>influence decisions</u> related to the outcome in question and they will be <u>required to pay</u> for that outcome"
  (*Contemporary Guidance for Stated Preference Studies*, Johnston et al. 2017)

policy consequentiality

payment consequentiality

Other dimensions of consequentiality?

E.g., pivotality?

Challenges with consequentiality

- **Consequentiality communicated** via survey scripts does not necessarily affect consequentiality perceptions (Czajkowski et al. 2017; Lloyd-Smith et al. 2019)
- How to **elicit consequentiality perceptions**?
  - A single general question: To what extent do you believe that the survey outcome will affect the decision of public authorities?
  - Questions differentiating between policy and payment consequentiality
  - More indicator (measurement) questions
- How to include data on consequentiality perceptions in **preference modelling**?
  - Endogeneity concerns: Self-reports on perceived consequentiality are likely driven by similar (unobservable) factors as stated preferences

Our study addresses these questions

Endogeneity of consequentiality perceptions

explored in previous studies

- Herriges et al. (2010) – an exogenous information treatment and a Bayesian treatment-effect model; importance of controlling for endogeneity
- No significant problem of endogeneity especially in studies using socio-demographics as instruments:
  - Vossler et al. (2012) – a generalized method of moments over-identification test
  - Interis and Petrolia (2014) – a two-step instrumental variable probit model
- Groothuis et al. (2017) – a bivariate probit approach; perceived consequentiality found to be endogenous; unobserved factors strengthen the consequentiality and decrease the likelihood of voting for the program
- Lloyd-Smith et al. (2019) – a special multi-step estimator for a scaled probit model; importance of controlling for endogeneity; with no endogeneity control, perceived consequentiality affects voting behavior, but the effect disappears with the special regressor

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Limitations:

- Little evidence – very few studies
- Mixed evidence
- Step-wise procedures
- Single indicator (measurement) questions for consequentiality

Endogeneity control in hybrid choice models

Budziński and Czajkowski (2020)

Model 1

- Standard hybrid choice models do not resolve endogeneity
- Two types of endogeneity:
  1) Latent variables are endogenous
  2) Indicator variables are endogenous, but latent variables are not

Model 2

- Solutions:
  – Directly modeling the correlation between latent variables and random parameters – help (1)
  – Adding a latent variable to capture the correlation caused by missing covariates – help (1) and (2)

Model 3

Measurement equations
(ordered probit)

Latent variables influence self-reports about beliefs in survey consequentiality

Latent variables

Unobserved beliefs about survey consequentiality

Discrete choice model
(interactions in the mixed logit model)

Latent variables influence stated preferences

Discrete choice experiment

- Public-good scenario: Extension of public theater offer in Poland (a number of shows)
- 4 choice tasks per person; CAWI; a representative sample of 2,863 residents of Poland

	Variant A	**Variant B** No changes	**Attribute levels**
Entertainment theaters	+ 25%	no change	+ 25%, + 50%, no change
Drama theaters	+ 50%	no change	
Children's theaters	no change	no change	
Experimental theaters	+ 50%	no change	
Annual cost for you (tax)	50 PLN	0 PLN	5, 10, 20, 50 PLN
Your choice	☐	☐	

Consequentiality elicitation

- Randomized statements assessed on a Likert scale with seven levels: from ‘definitely disagree’ to ‘definitely agree’ + don’t know
- Used in the measurement → 9 ordered probit models as measurement equations

I think that …
[1] … by participating in this survey, I will have influence on the future theater offer.
[2] … the results of this survey will determine if to change the theater offer.
[3] … the results of this survey will be used to decide if to change the theater offer.
[4] … if the theater offer is decided to be changed, the results of this survey will be used to decide which type of shows will be played more and less.
[5] … the increase of the theater offer as described in this survey is possible to be implemented.
[6] … a decision to expand the theater offer will indeed result in more shows and premiers, as described in this survey.
[7] … a decision to expand the theater offer will indeed result in higher (tax) fees, which will increase my household expenditures, as described in this survey.
[8] … I am one of many people participating in this survey, so my responses do not have a chance to affect the survey final results.
[9] … a decision whether to change the theater offer will be taken independently of the survey results.

Results

Measurement equations
(ordered probit)

Latent variables influence self-reports about beliefs in survey consequentiality

Latent variables

Unobserved beliefs about survey consequentiality

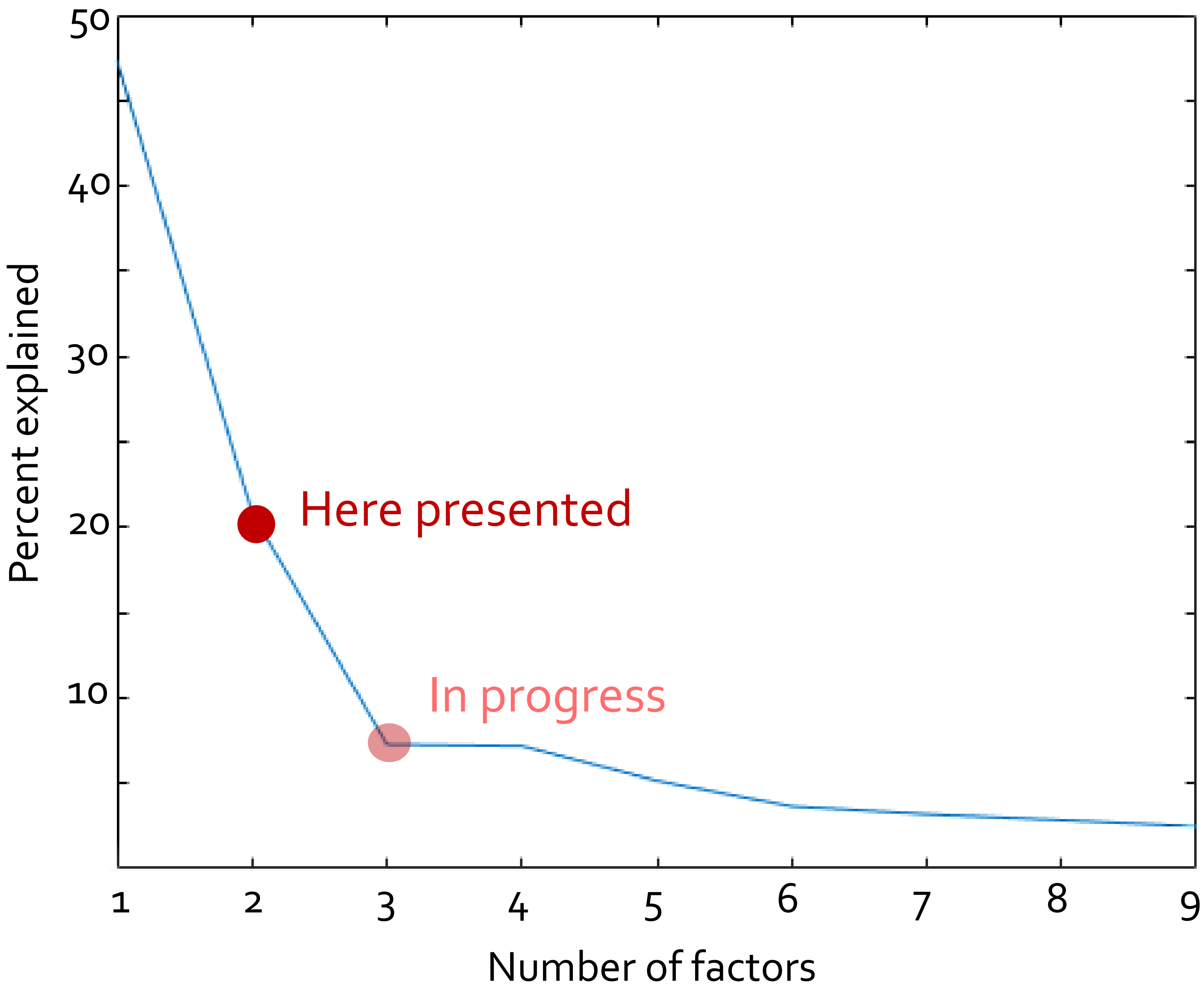
Discrete choice model
(interactions in the mixed logit model)

Latent variables influence stated preferences

	Model 1	Model 2	Model 3
	Standard	Corr. LVs and random parameters	+ 1 LV

How many latent variables to include?

How many dimensions of consequentiality do we have?



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Latent variables influence stated preferences

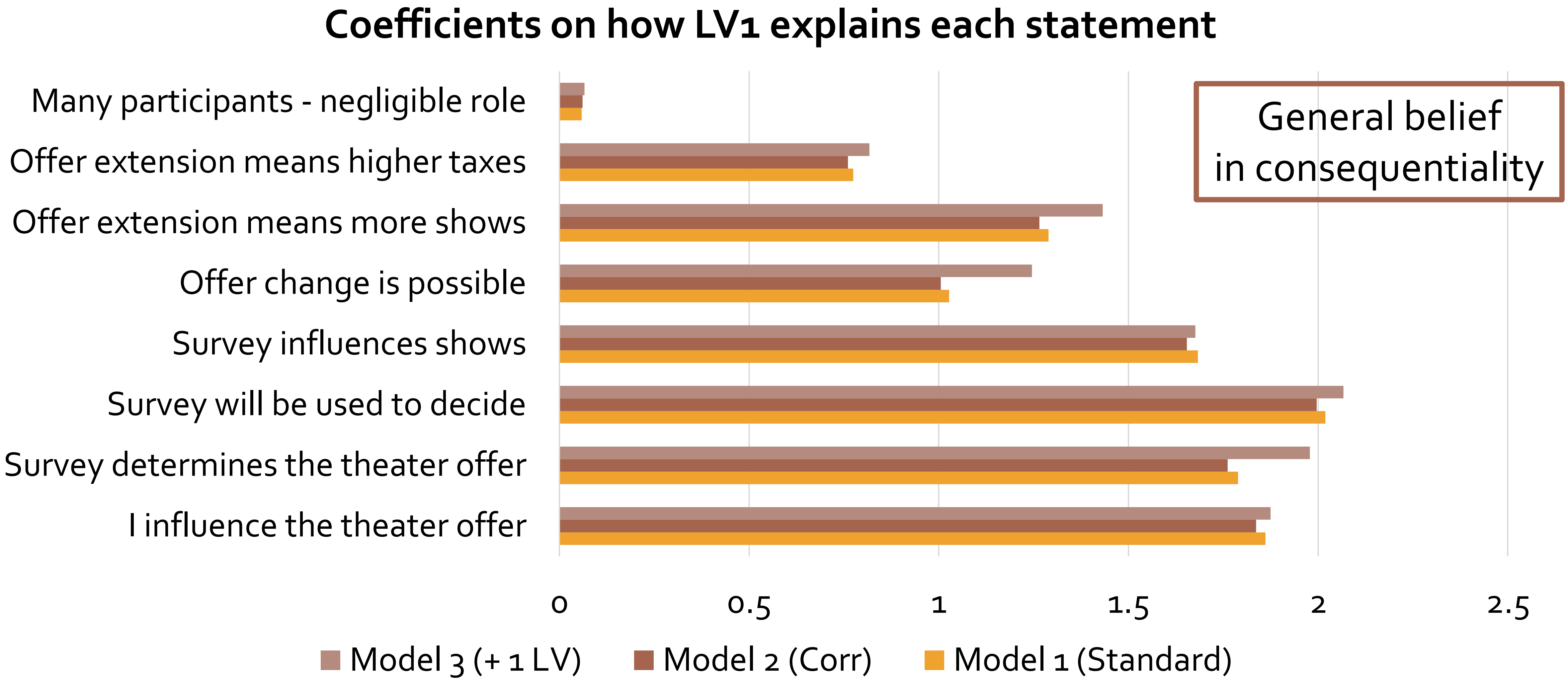
	Model 1	Model 2	Model 3
	Standard	Corr. LVs and random parameters	+ 1 LV
LL	-38,620.1	-38,564.6	-38,465.4
AIC/n	6.764	6.756	6.739

→ better → even better

- Responses to consequentiality statements are explained with latent variables
- Two latent variables (LVs) expressing perceived consequentiality:
  - General belief in consequentiality
  - Lack of belief in pivotality

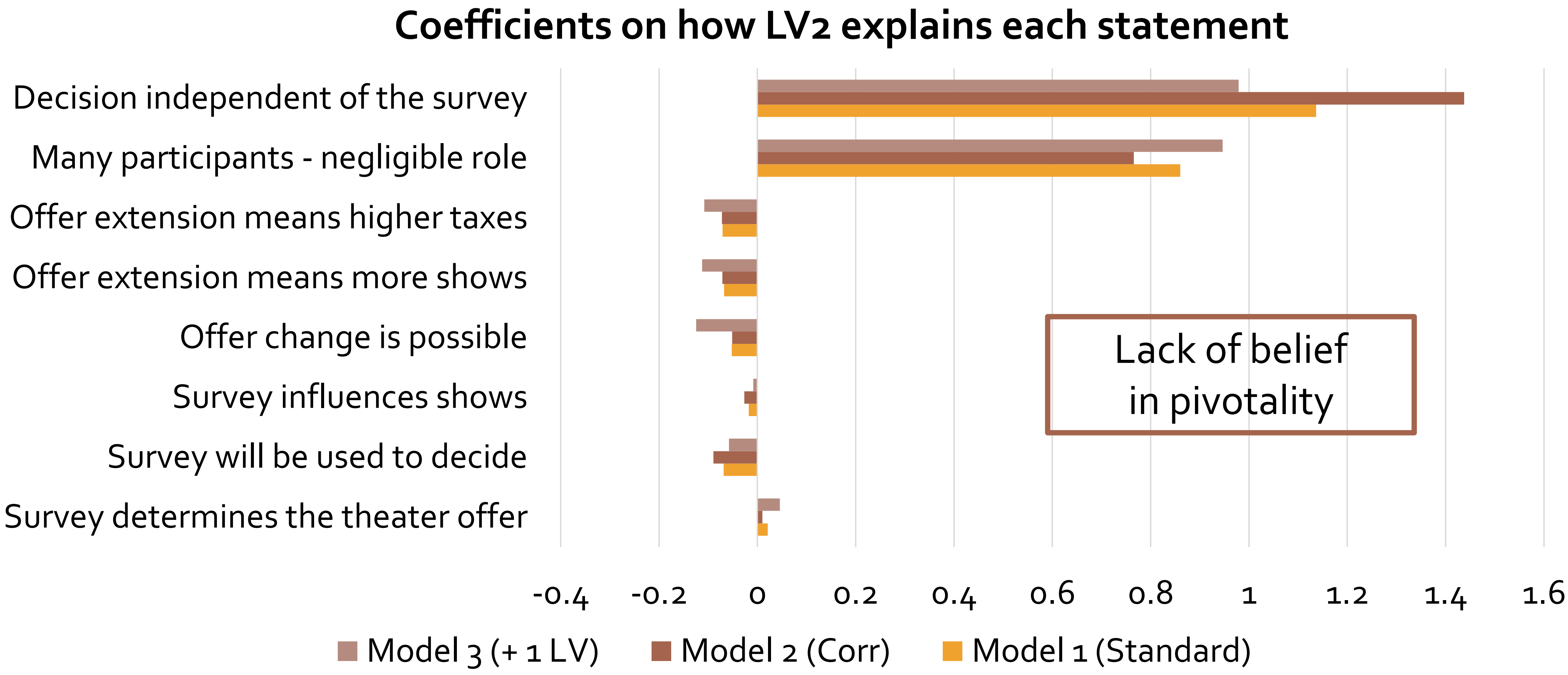
Results: Measurement equations

Ordered probits



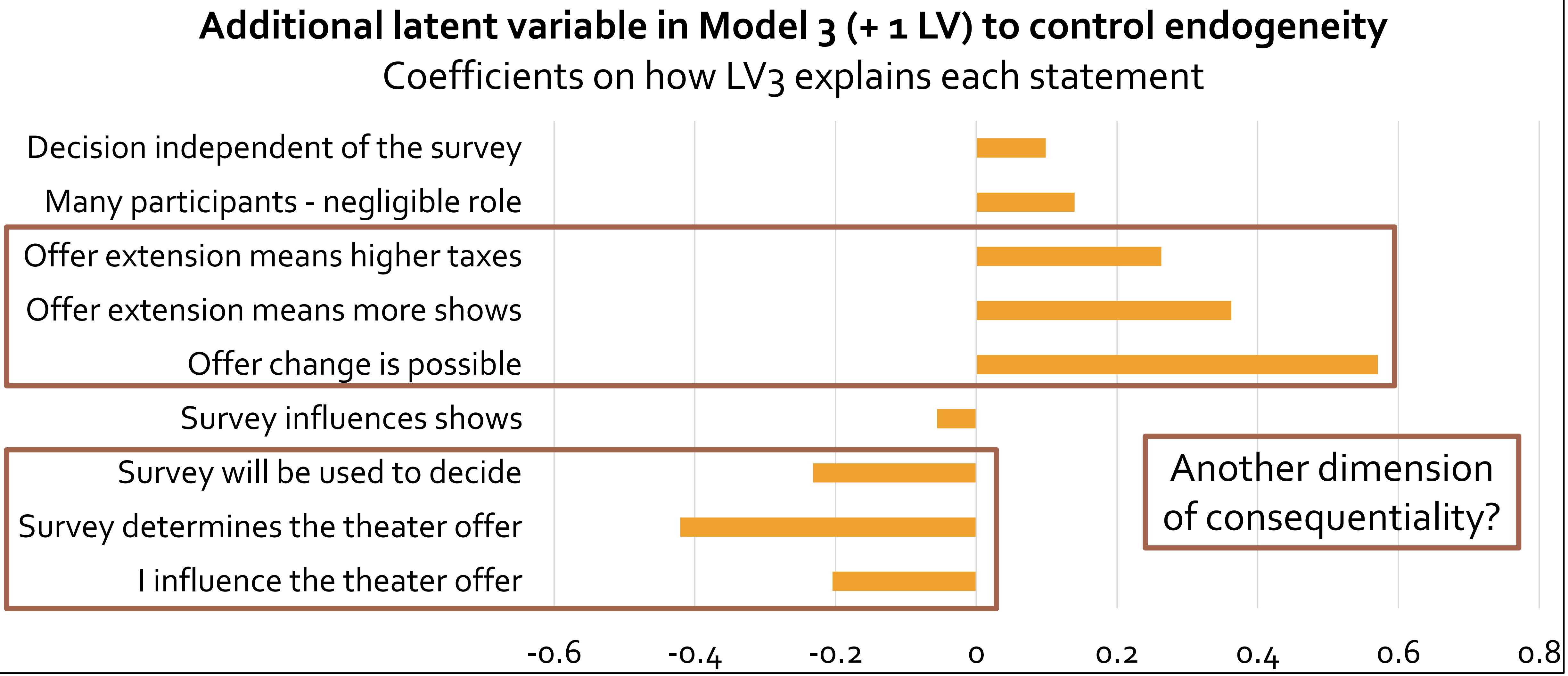
Results: Measurement equations

Ordered probits



Results: Measurement equations

Ordered probits



Results

Measurement equations
(ordered probit)

Latent variables influence self-reports about beliefs in survey consequentiality

Latent variables

Unobserved beliefs about survey consequentiality

Discrete choice model
(interactions in the mixed logit model)

Latent variables influence stated preferences

	Model 1	Model 2	Model 3
	Standard	Corr. LVs and random parameters	+ 1 LV
LL	-38,620.1	-38,564.6	-38,465.4
BIC/n	6.834	6.835	6.819

better

even better

- Two latent variables (LVs) expressing perceived consequentiality:
  - General belief in consequentiality
  - Lack of belief in pivotality

Results: Discrete choice component

Mixed logits with means interacted with LVs

Mean coefficient estimates

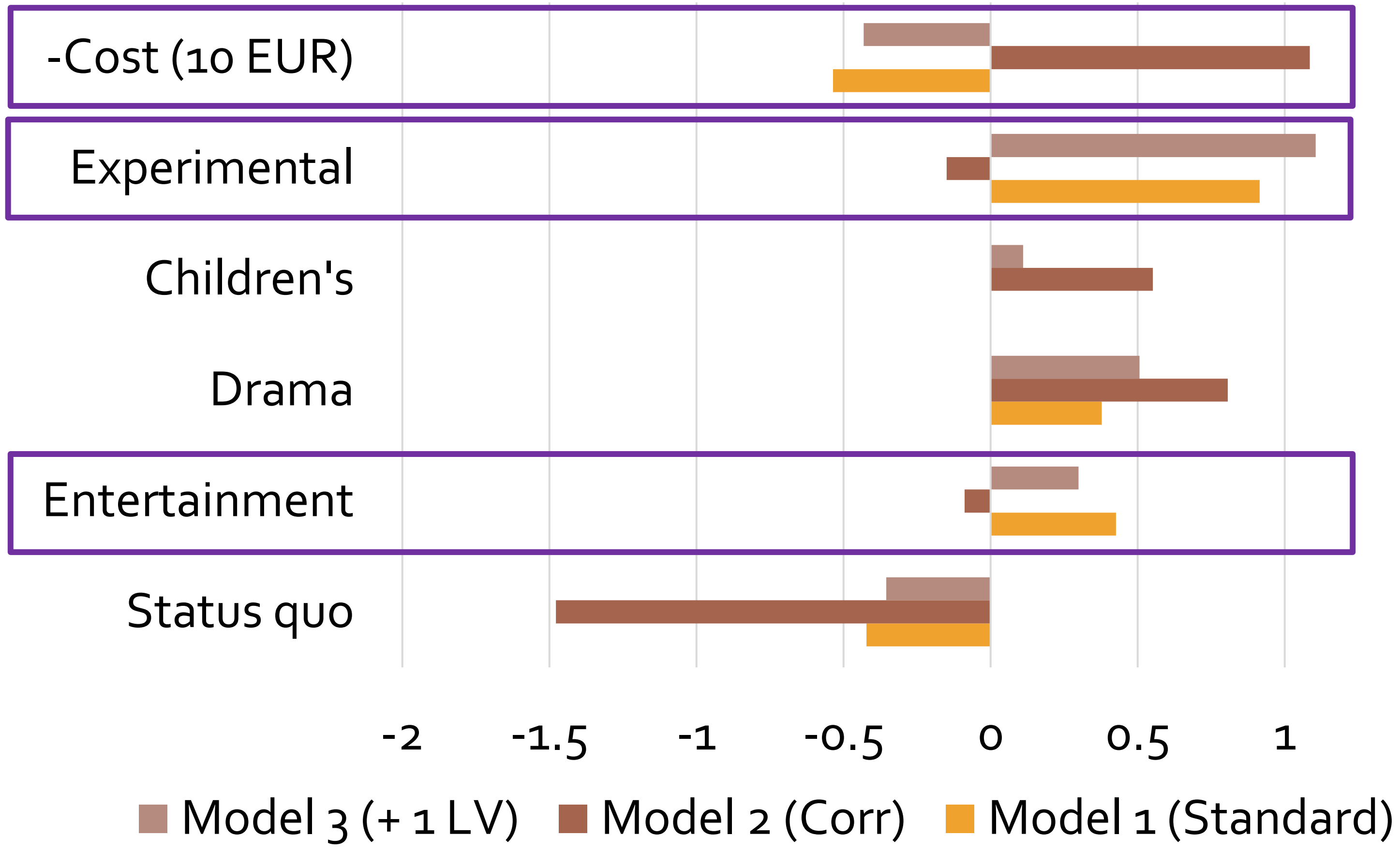
	Model 1	Model 2	Model 3
	Standard	Corr. LVs and random parameters	+ 1 LV
Status quo	0.4719***	0.4459***	0.4711***
Entertainment	0.8926***	0.999***	0.9151***
Drama	0.5769**	0.464*	0.4259
Children's	0.1364	0.1099	0.0443
Experimental	-0.4336	-0.502*	-0.409
– Cost (10 EUR)	3.7752***	3.8161***	3.6282***

- Preference parameters are random
- For all, standard deviations are (highly) significant
- Mean coefficient estimates are similar across models

Results: Discrete choice component

Mixed logits with means interacted with LVs

Coefficients of interactions of means with LV1 (general consequentiality)

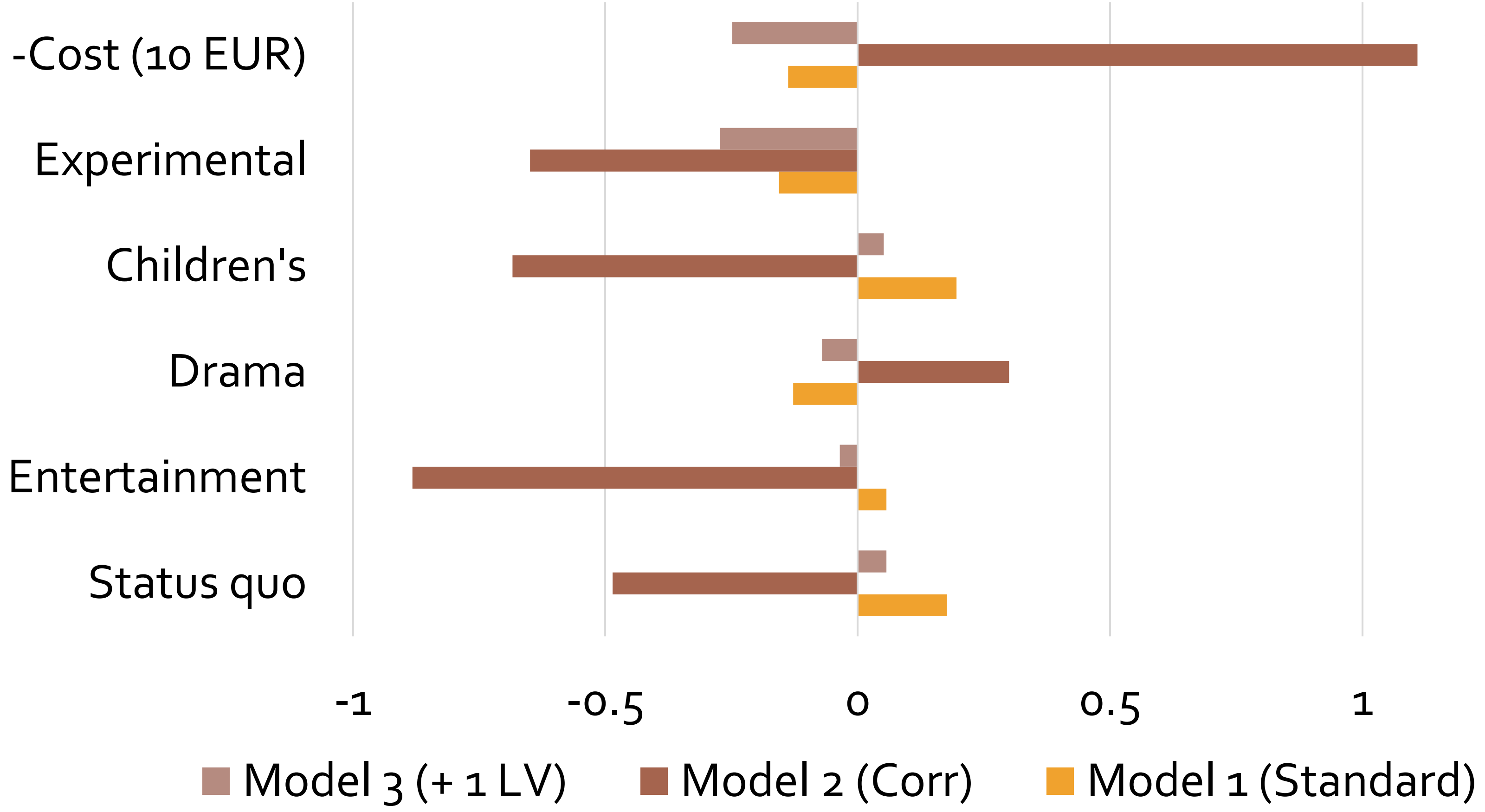


- Model 2 (Corr) accounts for one endogeneity type: endogeneity of the latent variable
- Endogeneity control matters largely for cost
- And so it changes willingness-to-pay values
- In Model 3 (+1 LV), maybe another consequentiality dimension? Does not fully account for residual correlation

Results: Discrete choice component

Mixed logits with means interacted with LVs

Coefficients of interactions of means with LV2 (pivotality)

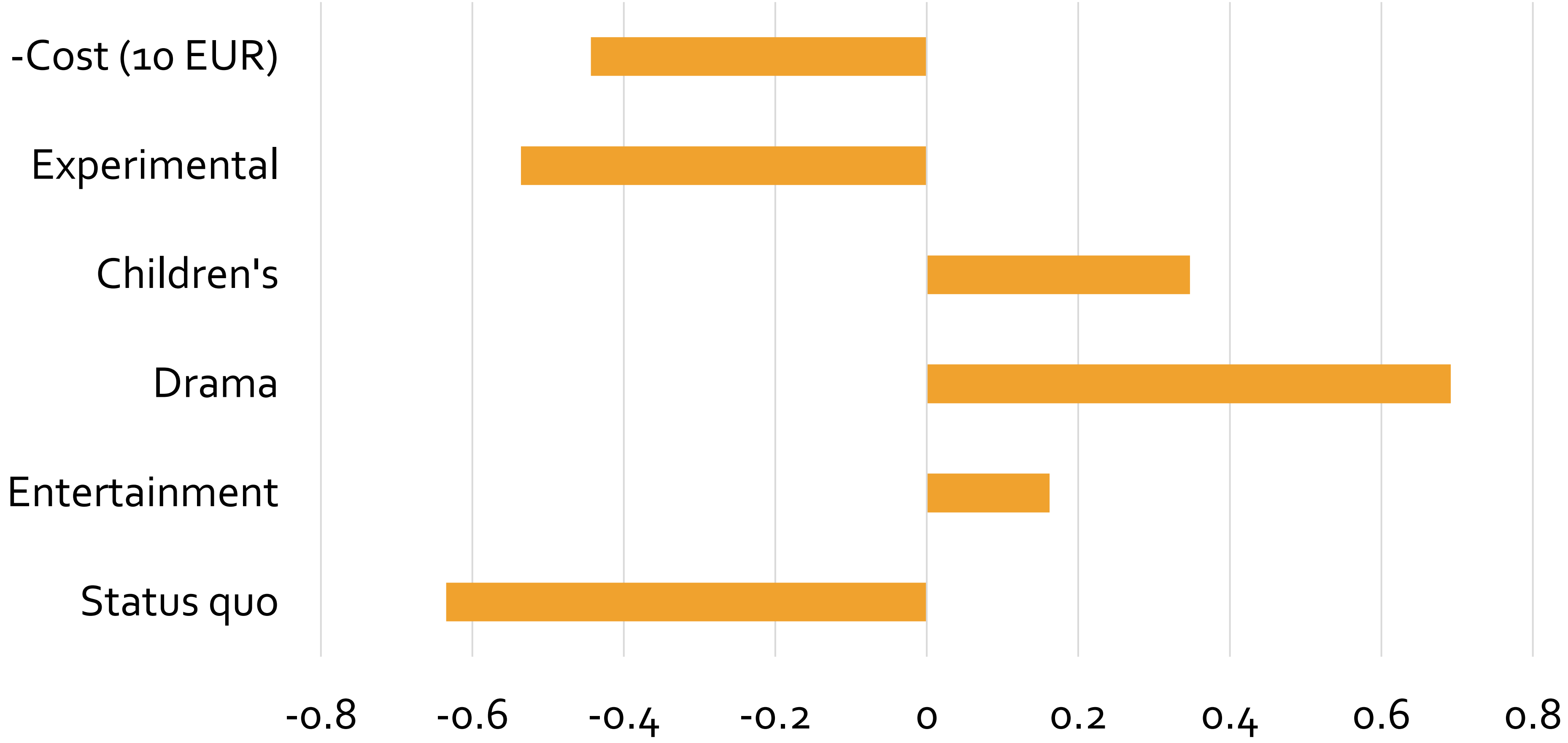


- Similar findings
- Endogeneity control in Model 2 matters for many attributes
- In Model 3, maybe another latent factor is needed?

Results: Discrete choice component

Mixed logits with means interacted with LVs

Coefficients of interactions of means with LV3



Closing thoughts

- Accounting for endogeneity matters
- The proposed solutions works well when we have well defined latent constructs
- No theory regarding dimensions of consequentiality (or other attitudes captured)
  - This could guide designing indicator questions to elicit respondents' perceptions
  - No construct validity
    - Theory does not predict what effect on preferences we should expect
- Maybe use some algorithm to find proper specification, similar to:
  - Paz, Alexander, Cristian Arteaga, and Carlos Cobos. "*Specification of mixed logit models assisted by an optimization framework.*" Journal of choice modelling 30 (2019): 50-60.
- Some problems with the interpretation of additional LVs
- Design an experiment to make causal inferences?

THANK YOU!

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