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ADDRESSING EMPIRICAL CHALLENGES RELATED TO THE INCENTIVE COMPATIBILITY OF STATED PREFERENCE METHODS

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Addressing empirical challenges related to the incentive compatibility of stated preference methods

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Abstract

An emerging theoretical literature focused on the incentive compatibility of stated preference surveys offers a new lens through which to view extant evidence on external validity, and provides guidance for practitioners. However, critical theoretical assumptions rest on latent respondent beliefs, such as the belief that respondents view surveys as potentially influencing policy (i.e., policy consequentiality), which gives rise to pressing empirical challenges. In this study, we develop a Hybrid Mixed Logit model capable of integrating multiple latent beliefs, and subjective measures of these beliefs, into discrete choice models of stated preferences. Further, we provide a split-sample test of the effects of exogenous information signals related to policy consequentiality. Our results suggest some potential for researchers to induce desired beliefs through simple information signals and, importantly, that latent beliefs and information signals significantly influence elicited willingness to pay.

Keywords:

discrete choice experiment; stated preferences; consequentiality; field experiment; hybrid mixed logit model

JEL:

C93, C35, H41, Q51

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1. Introduction

Stated preference surveys continue to be the leading approach for estimating the value of environmental and other public goods, especially those with passive use value. Although the methodology has been in use for over fifty years, concerns over the ability of surveys to provide valid welfare measures remain, serving as an obstacle to widespread adoption in the legal and policy arenas. Recently, theoretical work has identified conditions for a stated preference survey to be incentive compatible in the sense that it provides incentives for *truthful* preference revelation. These conditions for incentive compatibility rely heavily on *latent* (i.e., unobserved) respondent beliefs. For instance, when a single binary choice (SBC) question is used, respondents must perceive that the stated cost can be coercively collected upon implementation (i.e., “payment consequentiality”) and that a response in favor of the proposal weakly monotonically increases the chance of its implementation (i.e., “policy consequentiality”; Carson and Groves (2007); Carson *et al.* (2004); Vossler, Doyon and Rondeau (2012)). In addition to these beliefs, incentive compatibility for the increasingly popular repeated binary discrete choice experiment (binary DCE) requires respondents to believe that at most one of the proposed policies can be implemented and that the perceived implementation rule induces independence between choice sets (i.e., that a vote on one policy has no effect on the implementation probability of another policy; Vossler, Doyon and Rondeau (2012)). This study provides guidance on how to address two of the significant challenges that arise when undertaking empirical work that endeavors to satisfy and/or test the theoretical assumptions tied to respondent beliefs.

One empirical challenge is how to appropriately include stated measures of latent/unobservable beliefs, such as Likert-scale responses to a policy consequentiality question, into models of stated preferences. Direct inclusion of stated measures of beliefs may be problematic for two reasons. First, stated beliefs are measured imprecisely, giving rise to issues of measurement error. Second, stated beliefs may be correlated with other unobserved factors that influence choice. In prior work, Herriges *et al.* (2010) develop a Bayesian treatment effect model for SBC data that uses instrumental variables to identify the relationship between stated policy consequentiality on willingness-to-pay (WTP). Vossler, Doyon and Rondeau (2012) and Vossler and Watson (2013) briefly mention binary probit instrumental variable models, with the former study suggesting statistical evidence that measured beliefs can be considered exogenous and the latter citing a weak instruments problem. Here, we propose a

Hybrid Mixed Logit (HMXL) model, which models a belief as a latent variable in the utility function, ties the belief to observed covariates (e.g., individual characteristics) through a structural equation, and specifies a measurement equation where the stated belief is a function of the latent variable, thus recognizing the presence of measurement error. Relative to prior approaches for dealing with the possible endogeneity of stated beliefs in discrete choice models, the proposed HMXL model can be applied generally to both SBC and DCE data and can accommodate multiple latent beliefs. As with standard mixed logit models, the HMXL allows the analyst to incorporate various forms of preference heterogeneity. Identification relies on there being available measures of the latent variables rather than instrumental variables for the directly included (endogenous) stated belief measure(s).

A second challenge, assuming the theoretical conditions tied to beliefs are not universally met, is how to modify survey design to induce desired beliefs. In their critical review of the literature, Kling, Phaneuf and Zhao (2012) point out that “the effect of consequentiality scripts in stated preference surveys is in its infancy”. Using as an empirical application a binary DCE survey concerning public programs for discounted theatre tickets in Warsaw, Poland, we use a split-sample approach to investigate four information scripts that vary in their signals of policy consequentiality. The baseline treatment provides information at a level that is common in stated preference surveys, and the other treatments increase the frequency at which policy consequentiality is emphasized in the survey. As an ancillary benefit, this exogenous variation allows us to identify whether there is a *causal* effect of policy consequentiality on elicited values. As acknowledged in prior work, follow-up consequentiality questions are themselves *inconsequential* constructs. This opens up the possibility that identified correlations may be spurious and, similarly, that the drivers of consequentiality question responses may have little to do with actual beliefs.

In the field survey context, and in a similar spirit to our study, a few prior studies exogenously vary information provided to respondents with the intent of altering perceptions over policy consequentiality.¹ [Bulte et al. \(2005\)](#) find that providing a statement that alerts respondents that the results of the study “will be made available to policymakers, and could serve as a guide for future decisions” decreased WTP. Meyerhoff, Oehlmann and Merkle (2014)

¹ A handful of controlled experiment studies exogenously vary the level of policy consequentiality, for example, by manipulating the probability a vote is binding (Landry and List, 2007; Mitani and Flores, 2012; Carson, Groves and List, 2014), or by introducing treatments with and without regulator votes (Collins and Vossler, 2009; Vossler and Evans, 2009).

and Drichoutis *et al.* (2015), in contrast, find no effects tied to inclusion/exclusion of a consequentiality script. Herriges *et al.* (2010) make use of a published article that provided evidence that survey results directly affected related policy decisions in the past, and find that stated beliefs over policy consequentiality increase when respondents are provided this information. Both of these studies used SBC elicitation, and as such our exploration provides primary evidence on this type of inducement for DCE surveys. Further, the scripts we explore can further be easily incorporated into general practice. Indeed, it is presumably rare to have relevant media coverage available that provides a clear third-party link between surveys and policy. An ancillary benefit of the HMXL framework in this context is that it allows one to not only measure whether information signals alter stated beliefs but also whether such signals influence stated WTP.

The empirical study provides several important insights. First, similar to Vossler and Watson (2013), for our application we are not able to identify (strong) instrumental variables from the extensive information collected through the survey.² This provides further impetus for the proposed HMXL estimator. Second, we find that latent beliefs over policy consequentiality have a discernible effect on elicited WTP for the proposed discounted theatre ticket programs. Importantly, these latent beliefs are strongly correlated with measured beliefs, using as our measurement device a Likert-scale policy consequentiality question now prevalent in the literature. Third, WTP is significantly correlated with our information treatments that vary the signals of policy consequentiality, which emphasizes the empirical importance of the theoretical assumption regarding policy consequentiality; indeed, this can be taken as evidence in favor of construct validity. Fourth, somewhat surprisingly, the information treatments have no significant effect on *stated* beliefs. Thus, although the econometric results provide empirical support that a follow-up question about respondent beliefs over actual policy consequences provides useful information, the findings emphasize the importance of developing follow-up questions that elicit beliefs more precisely.

The remainder of the paper is organized as follows. The next section characterizes the innovative econometric approach, which is followed by a detailed description of the study provided in Section 3. The results are presented in Section 4. Section 5 concludes.

² In particular, we estimated a version of the mixed logit model that incorporated a control-function approach to deal with the potential endogeneity of stated perceptions of policy consequentiality. We refer the interested reader to Guevara and Ben-Akiva (2010) for a comparison of control-function and latent-variable approaches.

2. Econometric approach – the Hybrid Mixed Logit model

Hybrid choice models are very flexible tools that allow analysts to incorporate perceptions and cognitive processes into a Random Utility Model (RUM) framework. They thus provide a link between behavioral sciences (e.g., psychology) and fields oriented on estimation such as engineering and economics. As stated in Ben-Akiva *et al.* (2002), hybrid choice models are a general class of models which may include additional random disturbances in the form of error components or random parameters, psychological factors in the form of latent variables and preference heterogeneity, allowing for non-RUM decision processes in some of them.³ In this study we develop a Hybrid Mixed Logit (HMXL) model which combines the framework widely adopted for analyzing DCE data, the Mixed Logit (Revelt and Train, 1998), with the Multiple Indicators and Multiple Causes (MIMIC) model (Jöreskog and Goldberger, 1975).

Connecting discrete choice models with a MIMIC model is an emerging approach for incorporating psychological factors in the RUM framework. Most of the applications to date appear in the transportation literature (e.g., Johansson, Heldt and Johansson, 2006; Daly *et al.*, 2012; Daziano and Bolduc, 2013). Applications in the environmental literature include Hess and Beharry-Borg (2012), who incorporate latent attitudes towards coastal water quality protection in a model of stated preferences regarding watery quality improvements in Tobago, and Dekker *et al.* (2012), who treat preference uncertainty as a latent variable in a choice model of flood risk policies in the Netherlands.

In the context of our application, we consider a psychological factor – beliefs over policy consequentiality – as a latent variable that influences stated preferences. Note that the common practice is to instead include stated measures of consequences as explanatory variables in the choice model. Aside from endogeneity issues, the adoption of the HMXL model avoids a possible econometric problem associated with this practice; in particular, in many cases there are many indicators describing one psychological factor which can lead to a large number of estimable parameters in the model, collinearity and difficulty with the interpretation of results.

All hybrid choice models consist of three parts: a discrete choice model; structural equations; and measurement equations. Below we describe each part in turn. For our application, we consider one latent variable. For sake of generality, however, the proposed framework considers the possibility of a vector of latent, psychological variables. As previously

³ These models are sometimes labelled Integrated Choice and Latent Variable (ICLV) models.

noted, the incentive compatibility of a repeated DCE requires beliefs related to policy consequentiality, payment consequentiality and choice set independence. Although we did not collect data related to the latter two beliefs, such data can in fact be incorporated into a single framework in a straightforward fashion. The framework further allows the possibility that there are multiple measures available for any given latent variable.

2.1. Discrete choice model

The theoretical foundation for the discrete choice model is random utility theory, which assumes that the utility a person derives depends on observed characteristics and unobserved idiosyncrasies, represented by a stochastic component (McFadden, 1974). As a result, individual i 's utility resulting from choosing alternative j in choice set t can be expressed as:

$$V_{ijt} = a_i c_{ijt} + \mathbf{b}_i' \mathbf{X}_{ijt} + e_{ijt}, \quad (1)$$

where the utility expression is assumed additively separable in the cost of the alternative, c_{ijt} , and other attributes, $\mathbf{X}_{ijt}$; a_i and $\mathbf{b}_i$ denote estimable parameters; and e_{ijt} is a stochastic component allowing for factors not observed by the econometrician to affect individuals' utility and choices.

There are two aspects of the above specification to emphasize. First of all, a_i and $\mathbf{b}_i$ are *individual*-specific, thus allowing for heterogeneous preferences amongst respondents and leading to a mixed logit model (MXL).⁴ Assuming instead that parameters are the same for all respondents implies homogenous preferences and leads to the multinomial logit model (MNL) as a special case. Secondly, the stochastic component of the utility function (e_{ijt}) is of unknown, possibly heteroskedastic variance ($\text{var}(e_{ijt}) = s_i^2$). Identification of the model typically relies on normalizing this variance, such that the error term $\varepsilon_{ijt} = e_{ijt} \frac{\pi}{\sqrt{6}s_i}$ is i.i.d. type I extreme value with constant variance $\text{var}(\varepsilon_{ijt}) = \pi^2/6$. This leads to the following specification:

$$U_{ijt} = \sigma_i a_i c_{ijt} + \sigma_i \mathbf{b}_i' \mathbf{X}_{ijt} + \varepsilon_{ijt}. \quad (2)$$

⁴ It is typically assumed that individual parameters follow a particular distribution (possibly a multivariate distribution allowing for non-zero correlation of model parameters), rather than being separately estimated for each individual.

Note that due to the ordinal nature of utility, this specification still represents the same preferences. The estimates $\sigma_i a_i$ and $\sigma_i b_i$ do not have direct interpretation anyway, but if interpreted in relation to each other the scale coefficient ($\sigma_i = \pi / (\sqrt{6} s_i)$) cancels out.

Finally, given the interest in establishing estimates of WTP for the non-monetary attributes X_{ijt} , it is convenient to introduce the following modification which is equivalent to using a money-metric utility function (aka estimating the parameters in WTP space; Train and Weeks, 2005):

$$U_{ijt} = \sigma_i a_i \left(c_{ijt} + \frac{b_i'}{a_i} X_{ijt} \right) + \varepsilon_{ijt} = \lambda_i \left(c_{ijt} + \beta_i' X_{ijt} \right) + \varepsilon_{ijt} . \quad (3)$$

Note that under this specification the vector of parameters β_i is now scale-free and can be directly interpreted as a vector of implicit values for the attributes, X_{ijt} . Also, in MXL models an additional advantage of this specification is that the econometrician is able to specify a particular distribution of WTP in the population, by specifying the distribution of β_i , rather than the distribution of the underlying utility parameters (b_i).⁵

In our HMXL model we also assume that the random parameters β_i and λ_i depend on one latent variable, the unobserved belief over policy consequentiality. Although our empirical application focuses on one latent variable, the estimation framework generally allows for multiple latent variables to enter the analysis. In the exposition that follows, we assume there are a vector of individual-specific latent variables, denoted by $\mathbf{LV}_i$. The functional form of this dependence may vary due to distributional assumptions. In the analysis we use two distributions, normal (for all non-monetary attributes) and log-normal (for the cost attribute). For a normally distributed β_i , this dependence is of the form:

$$\beta_i = \Lambda' \mathbf{LV}_i + \beta_i^* , \quad (4)$$

⁵ As translating utility parameters into a money equivalent requires dividing them by a (possibly also random) cost coefficient, this can imply what are often implausible assumptions about the distribution of WTP (Carson and Czajkowski, 2013).

where Λ is a matrix of estimable coefficients and β_i^* has a multivariate normal distribution with a vector of means and a covariance matrix to be estimated.⁶ Similarly, we assume that the cost coefficient follows a log-normal distribution:

$$\lambda_i = \exp(\tau'LV_i + \lambda_i^*), \quad (5)$$

where τ is a vector of estimable coefficients and λ_i^* follows a normal distribution with the parameters describing its mean and standard deviation to be estimated.⁷ As a result, the conditional probability of individual i 's choices in choice set t is given by:

$$P(y_i | X_i, \beta_i^*, \lambda_i^*, LV_i, \Lambda, \tau, \theta) = \prod_{t=1}^{T_i} \frac{\exp(\lambda_i(c_{ijt} + \beta_i'x_{ijt}))}{\sum_{k=1}^C \exp(\lambda_i(c_{ikt} + \beta_i'x_{ikt}))}, \quad (6)$$

where θ is a vector of parameters on which λ_i^* and β_i^* depend.

2.2. Structural equations

We assume that latent variables depend on exogenous factors, such as socio-demographic variables, which are stacked in the vector X_i^{str} . This relationship can be described by the following structural equations:

$$LV_i = \Psi'X_i^{str} + \xi_i, \quad (7)$$

with Ψ representing a matrix of coefficients, and error terms ξ_i which are assume to come from a multivariate normal distribution with zero mean and a diagonal covariance matrix. This framework readily allows for multiple latent variables. For instance, beliefs over policy consequentiality and, in a DCE, independence of choice sets could be modelled as two distinct latent variables, assuming that measures of both are available.

⁶ The number of columns in Λ is equal to the number of latent variables and the number of rows equal to the number of non-monetary attributes.

⁷ λ_i^* can also be correlated with β_i^* .

2.3. Measurement equations

The main purpose of including latent variables in the models is that they are describing some psychological factors. These factors usually cannot be measured in a direct way, unlike other individual characteristics such as age and gender. Instead a researcher must use various indicator questions in a survey, responses to which could be expected to be determined by the latent variables.

The model choice for the indicator equations depends on the particular application.⁸ The measurement equations could be linear, ordered, binary, multinomial or count regressions – whatever fits an interpretation of each indicator best.

In this study we include one indicator of the latent belief over policy consequentiality of a survey, which was measured on a five-point Likert scale. The measurement equation is therefore modelled using ordered probit. In the general case with more latent variables and more (ordered) indicator variables $\mathbf{I}_i$, the measurement component of the hybrid choice model can be specified as follows:

$$\mathbf{I}_i^* = \mathbf{\Gamma}'\mathbf{L}\mathbf{V}_i + \boldsymbol{\eta}_i, \quad (8)$$

where $\mathbf{\Gamma}$ is a matrix of coefficients and $\boldsymbol{\eta}_i$ denotes a vector of error terms assumed to come from a multivariate normal distribution with zero means and an identity covariance matrix.⁹ Under this specification, the relationship between I_{il} and I_{il}^* (for the l -th indicator variable which takes J possible, ordered values) becomes:

$$\begin{aligned} I_{il} = 1, & \quad \text{if} & \quad I_{il}^* < \alpha_{1l} \\ \vdots & \quad \vdots & \quad \vdots \\ I_{il} = k, & \quad \text{if} & \quad \alpha_{k-1l} \leq I_{il}^* < \alpha_{kl}, \\ \vdots & \quad \vdots & \quad \vdots \\ I_{il} = J, & \quad \text{if} & \quad \alpha_{J-1l} \leq I_{il}^* \end{aligned} \quad (9)$$

where the α 's are the threshold parameters to be estimated for each indicator. This specification leads to the well-known ordered probit likelihood form for I_i :

⁸ Many early hybrid choice model applications used a simple, linear regression even in cases where the dependent variable was clearly ordered (Daly *et al.*, 2012).

⁹ It is important to note that the number of measurement equations need not equal the number of latent variables. For instance, cases may arise where more than one indicator for a latent variable may be available (e.g., there may be two survey questions targeting beliefs over policy consequentiality). This framework can accommodate such a setting by specifying multiple measurement equations for a single latent variable.

$$P(I_i | \mathbf{LV}_i, \mathbf{\Gamma}, \mathbf{\alpha}) = \prod_{l=1}^L (P(I_{il} | \mathbf{LV}_i, \mathbf{\Gamma}_l, \alpha_l)) = \prod_{l=1}^L (\Phi(\alpha_{kl} - \mathbf{\Gamma}_l' \mathbf{LV}_i) - \Phi(\alpha_{k-l} - \mathbf{\Gamma}_l' \mathbf{LV}_i)), \quad (10)$$

where $\Phi(\cdot)$ denotes the normal cdf, $\mathbf{\Gamma}_l$ and α_l are the l -th row of the $\mathbf{\Gamma}$ matrix and the vector of the threshold parameters for the l -th indicator variable, respectively.¹⁰

Finally, after combining equations **Błąd! Nie można odnaleźć źródła odwołania.**, **Błąd! Nie można odnaleźć źródła odwołania.** and **Błąd! Nie można odnaleźć źródła odwołania.**, we obtain the full-information likelihood function for our HMXL model, where for ease of exposition we stack the parameter vectors $\mathbf{\Lambda}, \mathbf{\tau}, \mathbf{\theta}, \mathbf{\Psi}, \mathbf{\Gamma}, \mathbf{\alpha}$ into the single vector $\mathbf{\Omega}$:

$$L_i = \int P(y_i | \mathbf{X}_i, \mathbf{X}_i^{str}, \mathbf{\beta}_i^*, \lambda_i^*, \xi_i, \mathbf{\Omega}) P(\mathbf{I}_i | \mathbf{X}_i^{str}, \xi_i, \mathbf{\Omega}) f(\mathbf{\beta}_i^*, \lambda_i^*, \xi_i | \mathbf{\theta}) d(\mathbf{\beta}_i^*, \lambda_i^*, \xi_i). \quad (11)$$

As random disturbances of $\mathbf{\beta}_i^*, \lambda_i^*$, as well as error terms in structural equations ξ_i are not directly observed, they must be integrated out of the conditional likelihood. This multidimensional integral can be approximated using a simulated maximum likelihood approach.¹¹

2.4. Identification

In order to make identification of hybrid choice models possible, the scale of every latent variable needs to be normalized (Daly *et al.*, 2012). This can be done by normalizing variances of the error terms in the structural equations or by normalizing some coefficients in the $\mathbf{\Gamma}$ matrix for each latent variable. Raveau, Yáñez and Ortúzar (2012) conducted a simulation study which indicates that normalizing variances leads to better convergence of the models, which results in the recovered estimates being closer to the data generating process used. Normalizing the variances of the error terms is thus the approach we adopt here. We normalize latent variables to have variance equal one ($LV_{ik}^{norm} = LV_{ik} / std(LV_k)$), which leads to setting the k -th

¹⁰ Note that this likelihood is a factor of likelihoods of each indicator separately. It is so due to the earlier assumption that $\mathbf{\eta}_i$ has an identity covariance matrix. This assumption is equivalent to assuming that whole correlation between indicator variables is explained by the latent variables used. However, this assumption can be relaxed, as in Bhat, Varin and Ferdous (2010).

¹¹ Our model assumes no correlations between the measurement, structural and choice components error terms. This is an issue which could potentially be pursued in the future to investigate if explicitly allowing for some of these correlations could improve the model performance or address the endogeneity issue better.

row of Ψ to $\Psi_k^{norm} = \Psi_k / std(LV_k)$ and the standard deviation of the k -th error term as $std(\xi_{ik}) = 1 / std(LV_k)$.¹²

Unfortunately it is not known if this condition is sufficient – identification depends on the number of latent variables and measurement equations. We followed Bollen and Davis (2009) to ensure the necessary condition for identification of structural equation models holds; in particular, the specification satisfies the “2+ emitted paths rule” (the LV has exactly one unique indicator in the measurement equation and is linked with six preference parameters in the discrete choice component). In addition, we tested our model by running simulations – we generated artificial datasets and validated our model by recovering the underlying parameters. Our model encountered no problems in identification and produces stable results.^{13, 14}

3. Stated preference survey and information treatments

3.1. Survey design

Our empirical study focuses on the public financing of municipal theatres in Warsaw, Poland. The survey scenarios considered describe proposed programs for discounted theatre tickets for Warsaw citizens, in particular programs that would result in a uniform ticket price of 5 Polish złoty (PLN) for a single admission,¹⁵ for four different categories of theatres defined by the type of productions they offer. Entertainment theatres stage light comedies and music shows. Drama repertory theatres aim at combining reading classics with ambitious comedies. Children’s theatres are focused on the youngest audience, while experimental theatres reject typical forms

¹² $std(LV_k)$ represents standard deviation of the k -th latent variable. Since we earlier used $\mathbf{LV}_i$ to represent a vector of all latent variables for individual i , LV_{ik} is a value of the k -th LV for individual i .

¹³ Econometric models estimated using maximum simulated likelihood approach are known to be relatively sensitive to starting values, optimization techniques and selecting convergence criteria. Our model is no exception in this respect and to make sure we reached the global maximum in optimization, we used different optimization methods, derived analytical gradient and used multiple starting points. In addition, since using longer low-discrepancy sequences (as opposed to shorter sequences or using pseudo-random draws) has been found to facilitate reaching the global optimum or revealing identification problems (Chiou and Walker, 2007; Czajkowski and Budziński, 2015) in simulation of the log-likelihood function, we used 10,000 Sobol draws with random linear scramble and random digital shift.

¹⁴ The code used for estimating the HMXL model, and the data in this study are available to researchers upon request.

¹⁵ During the time frame the survey was administered, 1 PLN $\approx$ 0.25 EUR $\approx$ 0.33 USD.

to introduce an alternative perspective into the performing arts. The proposed payment vehicle is an additional annual tax levied on citizens of Warsaw. As all of about 50 municipal theatres in Warsaw are already subsidized by the city on the order of 40-60%, the scenarios can be seen as increasing the provision of a public good and, as was confirmed during pretesting of the survey instrument, was found credible by respondents. The cost amounts considered are 10, 20, 50 and 100 PLN per year.

With the objective of estimating the demand for programs involving varying opportunities for discounted theatre tickets, we adopt a binary DCE approach. In particular, each choice set includes the status quo and one policy alternative.¹⁶ However, given the scant evidence available, there is not yet consensus regarding external validity. Figure 1 presents an example choice set. With four theatre categories and cost, there are five choice set attributes. With two levels for each theatre attribute (i.e., the reduced ticket pricing is either offered or not), and four possible cost amounts, the associated full factorial design gives rise to $2^4 \times 4 = 64$ choice sets.

The policy alternatives were generated following a Bayesian D-efficient design optimized for the MNL model (Scarpa and Rose, 2008), with priors for the choice parameters obtained from a pilot study administered to a sample of 119 respondents. In particular, we generated three “blocks” of 12 choice sets, and respondents were randomly assigned one of the blocks. To control for order effects, we randomized across respondents the order the choice sets were presented as well as the order in which the theatre attributes appeared in the choice set.

The survey begins with socio-demographic questions, and “warm-up” questions gauging respondents’ interest in culture and participation in cultural events. This is followed by a discussion of possible discounted theatre programs, including descriptions of the four theatre types, the proposed funding mechanism, and a typical reminder about budget constraints. A sequence of 12 choice tasks are then presented, where respondents are instructed to indicate their preference between the proposed program and the status quo for each.

At the end of the survey, participants are asked to indicate their beliefs concerning policy consequentiality (hereafter, *stated consequentiality*), in addition to typical follow-up questions (e.g., gauging motivations for choices, attitudes towards the financing of Warsaw theatres, etc.). The wording of the policy consequentiality question is (translated from Polish):

¹⁶ [Vossler, Doyon and Rondeau \(2012\)](#) identified conditions for incentive compatibility of this elicitation approach, and in their complementary field experiment found favorable evidence of external validity conditional on policy consequentiality holding empirically.

“To what extent do you agree with the statement that the results of the survey will influence future decisions regarding financing municipal theatres in Warsaw?”. The level of respondents’ agreement is measured on a five-point Likert scale (from 1 – “definitely disagree” to 5 – “definitely agree”).

3.2. Experimental information treatments

In order to examine the effect of consequentiality scripts, we introduce four treatments, which vary with respect to the exposition of significance of the survey results for the final decision to go ahead with the program (hereafter, *signaled consequentiality*). Table 1 presents the information provided in the various treatments. Each respondent participated only in a one treatment to which they were randomly assigned.

Consistent with survey design principles (Dillman, Smyth and Christian, 2014), it is common for surveys to emphasize the importance of the individuals’ response, as well as the social usefulness of the survey, which often includes statements that results will be provided to government officials. In other words, standard survey practice involves using language that may promote beliefs of policy consequences. In accordance with standard practice, regardless of treatment, the preamble script to our survey indicates that the survey is being conducted by researchers at the University of Warsaw, and the purpose of the survey is to collect information on opinions regarding the financing of Warsaw theatres. Treatment 1 (T1) does not provide any additional information. The survey instrument in T2, at the very beginning of the survey, states that respondents’ choices might influence future policies. As such, either T1 or T2 is likely to characterize the typical written (or verbally articulated) information signals related to policy consequentiality provided in most stated preference surveys.

The remaining treatments, T3 and T4 magnify the information signal through the inclusion of additional language within the survey instrument. T3, in addition to the information provided in T2, reminds respondents of possible ties to actual policy in the context of providing background information relevant for the proposals. T4 includes all the information from T3, and adds an inducement immediately before the value elicitation questions, and after the budget constraint reminder.¹⁷

¹⁷ We note that none of the information provided is deceptive. Relevant institutes (e.g., Office of Culture of Warsaw) were made aware of the study and our results are in fact being disseminated to them.

3.3. Survey implementation

The survey instrument is the outcome of extensive pretesting including individual interviews with potential survey respondents (verbal protocols) and a pilot study performed on a group of 119 Warsaw citizens. The survey was administered by a professional polling agency using Computer Assisted Web Interviews. Screening questions were used to restrict potential respondents to include only adult citizens of Warsaw who live in Warsaw and pay taxes there. Quotas were implemented in order to obtain a close match of the treatment subsamples with the adult population of Warsaw with respect to gender, age, education and household size.

Data was collected in February and March 2014. In total, there are 1,700 respondents.¹⁸ Detailed socio-demographic characteristics for each treatment sample and the adult population are presented in Table 2. As evident from the table, the targeted sampling strategy worked well to match the survey sample and population in terms of key demographics. However, since we cannot rule out important differences in unobservable factors between the sample and the population, we make no claim regarding sample representativeness. We nevertheless have clean identification of information treatment effects given random treatment assignment.

4. Results

Using data from the stated preference survey, we apply the HMXL model detailed in Section 2. The structure of the model is illustrated in Figure 2 and the estimation results for the primary specification presented in Table 3. Overall, the model explicitly incorporates the link between *signaled consequentiality*, *stated consequentiality*, respondents' observed preferences and their socio-demographic characteristics into one, jointly estimated, framework.

The latent variable considered is the belief over the policy consequentiality of the survey. Hereafter we refer to the latent variable as *latent consequentiality*. Through the specification of the structural equation, we link *latent consequentiality* to a number of respondent socio-demographic characteristics, specifically: an indicator for completion of high school or vocational school, *Edu2*; an indicator for university education, *Edu3*; respondent's *Age*; the number of children living in the household, *Children*; an indicator of gender that equals one if the respondent is female, *Female*; and household income, *HH income*. In the estimation,

¹⁸ As reported by the polling agency, the response rate in our survey was 29%.

each of these variables is standardized to have zero mean and unit standard deviation. Therefore, by construction, the expected value of the latent variable is also zero. Placing variables on similar scales is known to help with convergence properties of numerical algorithms and allows for convenient interpretation of the relative importance of each explanatory variable. The ordered probit measurement equation links *latent consequentiality* with respondents' choices to the Likert-scale question regarding policy consequentiality.

The HMXL model explains stated choices from the binary DCE as a function of attributes, latent beliefs over policy consequentiality, and our exogenous information signals tied to policy consequentiality. Given that the four attributes each have two levels, we control for these using binary indicators. An indicator, *Status quo*, is included to allow for differences in unobserved utility associated with choosing the status quo option relative to a proposed program. The latent variable and information signals appear as linear functions of the random coefficients tied to the policy attributes and the status quo indicator, and appear in an exponential function defining the random coefficient λ_i . The variation in information signals is collapsed into a single linear variable (i.e., the variable takes on the values 1 through 4) – *signaled consequentiality*.¹⁹ In the estimation we normalize the variable to have zero mean and unit standard deviation.

The first panel of Table 3 presents the results for the structural equation of the latent variable. The model suggests that females and higher household income respondents perceive the survey as more consequential, similarly to younger respondents. Higher levels of education have, if anything, a marginally significant impact, whereas having children does not significantly influence the latent variable.

In the next panel, the results of the measurement equation are reported. In addition to the estimates of the thresholds of the ordered probit model, we find that *latent consequentiality* significantly increases respondents' reported level of agreement with the statement that the survey results will indeed be used in designing future policies. This result thus suggests there is a causal link between latent beliefs over policy consequentiality and stated assessments of it.

The third panel of Table 3 reports the results of the discrete choice (mixed logit) component of the model. The model is specified in “WTP-space” and, accordingly, preference

¹⁹ Table A1 in the Reviewer Appendix presents a parallel model where instead we enter the information treatments into the choice model as separate treatment-specific indicators. The results justify the use of a single (linear, normalized) indicator of the signaled consequentiality which allows for easier interpretation of our results.

parameters can be directly interpreted in terms of WTP differences, in PLN.²⁰ Noting that the expected value of *latent consequentiality* and *signaled consequentiality* are both zero, the main effect for a particular theatre type is the estimate of the change in WTP associated with inclusion of the theatre type in the proposed program. Specifically, the model suggests that respondents, on average, are willing to pay the most – 33 PLN more per year – for a program that includes discounted tickets to entertainment theatres, followed by 21 PLN for drama repertory theatres, and about 10 PLN each for children’s and experimental theatres. The main effect corresponding with the status quo option is insignificant, although the large and significant estimated standard deviation of the random parameter suggests substantial heterogeneity in individual preferences in this respect. In fact, all estimated standard deviations are both relatively large and statistically different from zero, providing evidence of significant preference heterogeneity and, accordingly, justification for the mixed logit relative to the restrictive multinomial logit.

From the perspective of evaluating the influence of consequentiality on respondents’ observed preferences, the most interesting results are tied to the effects that *latent* and *signaled consequentiality* have on the WTP for program attributes. For all four theatre types, the interactions with *latent consequentiality* are statistically significant and positive, indicating that a stronger belief in policy consequentiality is correlated with higher WTP for these attributes. As additional evidence that *latent consequentiality* is a catalyst for a policy change, those with stronger beliefs have lower WTP for maintaining the status quo. Stronger latent beliefs over policy consequentiality has the additional effect of decreasing the scale of the unobserved component of utility (λ_i).

The interactions with *signaled consequentiality* show that providing more information about the survey results potentially being used to shape new policies results in significant increases of respondents’ WTP for entertainment theaters and drama theaters, and decreases the scale of unobserved utility. These findings thus largely mirror those based on *latent consequentiality*. However, the magnitudes of the effects are much smaller for the information signals. One interpretation of this result is that beliefs over policy consequences may largely be “homegrown” and entrenched, providing little room for the researcher to significantly influence them.

²⁰ The cost parameter is different, as it represents the scale of the unobserved component of utility ($\lambda_i = \sigma_i a_i$) and hence does not have a money-metric interpretation. Also, note that the cost parameter was assumed to be log-normally distributed and the results report the mean and the standard deviation of the underlying normal distribution, for costs which are expressed in negative 100 PLN.

To place the effects of latent beliefs and the information treatments into better perspective, Table 4 and Table 5 provide the simulated WTP changes associated with *signaled* and *latent consequentiality*, respectively. The results tied to *latent consequentiality* are quite dramatic. Even when comparing the WTP for program attributes across respondents in the 25th and 75th percentiles, WTP increases by a factor of two for children’s theatres, by a factor of four for drama theatres, by a factor of five for entertainment theatres and by a factor of seven for experimental theatres.

4.1. Importance of stated indications of policy consequentiality

Although *stated consequentiality* does not directly appear in the stated choice model, through simulation we can determine how WTP varies based on stated indications of beliefs over policy consequentiality. These results are provided in Table 6. Overall, the results suggest that considerable information on preferences is conveyed through this simple indicator for policy consequentiality. Indeed, WTP for program attributes are negative or statistically zero at the two lowest levels of *stated consequentiality*, and become positive and larger for higher levels. This positive relationship between stated consequentiality and elicited WTP mirrors the common finding in the literature (e.g., Herriges *et al.* (2010)). Similar to [Vossler, Doyon and Rondeau \(2012\)](#), we find a continuous relationship, rather than the “knife-edge” distinction between those with *inconsequential* beliefs and those with *consequential* beliefs (regardless of intensity). Such a “knife-edge” result is predicted by the theory, and found in the field survey studies of Herriges *et al.* (2010) and Vossler and Watson (2013). One explanation for this divide are behavioral differences due to the elicitation format; i.e., the latter two studies involved SBC rather than binary DCE elicitation.

4.2. Alternative model specifications

While moving from a MXL to a HMXL model allows for richer specifications, potentially avoiding estimation biases, the analyst must make additional choices as it pertains to the specification of the structural and measurement equations. In order help assess the sensitivity of our results to these specification choices, as well as to gain further insight, we estimated several additional models and include them in Tables A2 – A6 in the Reviewer Appendix.

In the models presented in Table A2 and Table A3, the measures of the information signals enter the structural equation as explanatory variables, instead of being interacted directly with the choice attributes. We find that the information signals significantly increase *latent consequentiality*, and indirectly, through latent beliefs, continue to significantly increase WTP.

The models included in Table A4 and Table A5 additionally include the information signals in the measurement component in the model, using normalized or dummy coded information treatment variables, respectively. We find that the *signaled consequentiality* levels are not significant explanatory variables in the ordered probit component of the HMXL model. Congruent with this result, as illustrated in Table 7, the raw data suggests that the information treatments did not systematically alter stated beliefs. In particular, using a Pearson chi-squared test, we fail to reject the null hypothesis that the frequency distributions for the four treatments are equal ($\chi^2_{(12)} = 6.759, p = 0.873$). Given that we previously established an important link between information treatments and elicited WTP, the implication here is that the Likert-scale question did not capture adequately the effects of the information treatments. One possibility is that the five-point Likert scale we used may not be precise enough to identify important distinctions.

Finally, Table A6 provides a version of the model which excludes all variables from the structural equation. Given that there are no meaningful differences in the choice model coefficients relative to those in our primary model, this provides evidence that the previously illustrated results regarding *latent consequentiality* is not simply an artefact driven by preference heterogeneity tied to socio-demographic characteristics. In fact, the results of all our models consistently point to the importance of *stated*, *latent* and *signaled consequentiality*, while demonstrating that these three variables are not necessarily fully correlated nor easily measured.

5. Discussion

Using a novel Hybrid Mixed Logit (HMXL) model, this study provides primary empirical evidence that, consistent with mechanism design theory, latent beliefs regarding the policy consequentiality of a binary DCE survey are an important driver of stated preferences. In fact, we find the effects to be very pronounced, with beliefs supporting policy consequentiality leading to substantially higher estimates of willingness to pay. Importantly, we find that the emerging approach for identifying beliefs – i.e., a simple Likert-scale survey

question – provides a measure that is, in fact, strongly correlated with latent beliefs. Recognizing that the direct inclusion of stated belief measures in choice models can give rise to econometric issues related to measurement error and simultaneity, the novelty of the HMXL model is that it allows latent beliefs to enter directly into the choice model while incorporating measurements of beliefs.

We further find that exogenous signals of policy consequentiality, provided through randomized information treatments, influence latent beliefs and likewise lead to meaningful increases in elicited WTP. However, the magnitude of the effect of *signaled consequentiality* on WTP is small in comparison to the effect of *latent consequentiality*. That our information treatments had only a small effect suggests some possibilities. First, it may very well be the case that in this and other field survey applications beliefs over policy consequentiality may naturally emerge. Stated preference, non-market valuation surveys are often of high quality, relate to socially important topics and describe plausible policy interventions. It thus may be instinctive for respondents to believe that, even if left unstated, policymakers are either funding the study or otherwise care about its outcomes. Second, even in settings where beliefs over policy consequentiality are weak, the range of possibly relevant information signals (i.e., the tools to convince respondents about potential actual consequences following from the survey outcomes) is necessarily constrained. That is, barring some exceptional circumstances, survey researchers cannot assure respondents that results will absolutely inform policy nor precisely define the mechanism by which this would occur. These arguments do, in turn, suggest that it may be interesting to explore consequentiality in opportunistic settings where, in the absence of researcher interventions, beliefs over consequences would be low (e.g., this could reflect scenarios involving weak institutions or issues with weak political support); or, alternatively, in studies where it is possible to establish and convey a link between survey results and policy decisions (see, for example, Johnston, 2006). It is further possible that, at least for some people and some settings, beliefs about potential citizen involvement in policy making may be very entrenched, and researchers are thus unlikely able to alter them.

A somewhat surprising result is that while we can establish a link between our information treatments, latent beliefs and WTP, there is no detectable relationship between the information treatments and our stated measure of policy consequentiality. This provides evidence that there is potential merit in formulating and investigating alternative belief elicitation questions. We note that although the inclusion of policy consequentiality questions in surveys is fairly new, there has already been reasonable variation in terms of the specificity

of the question as well as the measurement scale used. To our knowledge, no study has explored the effects of varying the policy consequentiality measure across split samples.

Our exploration of policy consequentiality targets just one of the beliefs identified by theory as being important for truthful preference revelation. Another important, latent belief is that payment can be collected from them upon program implementation. This assumption has received less attention, although efforts have begun to explore the use of follow-up questions to elicit information tied to this belief. The HMXL model developed here provides an estimation framework that accommodates the joint modelling of choices and responses to a multitude of survey questions charged with measuring beliefs, regardless of whether these questions are targeted towards the same belief or different sets of beliefs. In fact, related to the development of belief elicitation questions, the HMXL model can be used to determine the magnitude of the relationship between elicited and latent beliefs, thus providing a platform from which to discriminate and evaluate alternative approaches. The econometric framework further provides a way to determine the relative importance of distinct psychology factors – tied to different beliefs relevant for incentive compatibility or otherwise – on elicited values.

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Table 1. Information signals about consequentiality across treatments

Information statement	T1	T2	T3	T4
At the very beginning of the survey: “Your answers may be used in planning future policies of financing theatres in Warsaw.”		included	included	included
By the general information on financing the city theatres: “Warsaw citizens might have an impact on the work of city theatres [as they are subsidized from the city budget]. This survey aims at finding out Your opinion on the city theatres, and its results will allow to determine how the city of Warsaw should finance them.”			included	included
Near the description of the proposals: “Your answers in this survey will allow us to assess whether introduction of such a program is a good idea.”			included	included
Directly before the value elicitation exercise, presented in a frame: “ATTENTION – Please, remember that Your answers might be used for planning the future financing of Warsaw theatres. In the case of an introduction of any policy, which can be influenced by the survey results, the changes will involve all citizens (including You).”				included

Note: all passages translated from Polish.

Table 2. Socio-demographic characteristics of survey information treatment samples and population

Variable	T1	T2	T3	T4	Adult population of Warsaw
Female (proportion)	0.55 [0.50]	0.52 [0.50]	0.53 [0.50]	0.55 [0.50]	0.54
Age (in years)	44.90 [16.79]	43.32 [16.00]	43.73 [16.46]	43.71 [15.83]	43.92
Education attainment (share)					
Elementary school	0.07 [0.25]	0.06 [0.23]	0.06 [0.23]	0.07 [0.25]	0.16
Vocational pre-high school	0.09 [0.29]	0.12 [0.32]	0.09 [0.28]	0.09 [0.29]	
High school	0.30 [0.46]	0.31 [0.46]	0.32 [0.47]	0.35 [0.47]	0.43
Vocational school	0.11 [0.32]	0.12 [0.32]	0.12 [0.32]	0.10 [0.30]	
University	0.43 [0.49]	0.40 [0.49]	0.41 [0.49]	0.40 [0.49]	0.41
Household size (individuals)	2.97 [1.20]	2.98 [1.22]	2.86 [1.21]	3.03 [1.18]	2.87
Number of respondents	446	416	419	419	

Note: standard deviations appear in square brackets.

Table 3. HMXL model investigating the role of policy consequentiality

Structural equation (linear regression)				
dependent variable: <i>latent consequentiality</i>				
	Coefficient	Std. err.		
<i>Edu2</i>	0.1531*	0.0896		
<i>Edu3</i>	-0.0300	0.0896		
<i>Age</i>	-0.0037**	0.0019		
<i>Children</i>	0.0143	0.0443		
<i>Female</i>	0.2992***	0.0615		
<i>HH income</i>	0.1272***	0.0312		
Measurement equation (ordered probit)				
dependent variable: <i>stated consequentiality</i>				
	Coefficient	Std. err.		
<i>Latent consequentiality</i>	0.1762***	0.0361		
Threshold parameters:				
α_1	-1.6173***	0.0512		
α_2	-0.7364***	0.1570		
α_3	0.6206***	0.1575		
α_4	1.5957***	0.1587		
Willingness-to-pay model (mixed logit)				
	Means – main effects	Means – interactions with <i>latent</i> <i>consequentiality</i>	Means – interactions with <i>signaled</i> <i>consequentiality</i>	Standard deviations
	Coefficient (s.e.)	Coefficient (s.e.)	Coefficient (s.e.)	Coefficient (s.e.)
<i>Status quo</i>	2.5542 (1.6409)	-6.1479*** (1.9452)	1.0524 (1.4199)	43.7707*** (1.5122)
<i>Entertainment theatres</i>	32.5576*** (1.2731)	32.9290*** (1.8254)	3.9768*** (1.1878)	5.4877 (4.3528)
<i>Drama theatres</i>	20.8851*** (1.0256)	18.8256*** (1.4931)	3.4792*** (1.0029)	11.6298*** (1.6107)
<i>Children’s theatres</i>	10.5138*** (0.9683)	5.2935*** (1.4564)	0.4765 (0.9424)	15.3949*** (1.2652)
<i>Experimental theatres</i>	9.7442*** (0.9634)	10.7760*** (1.4881)	-0.1184 (0.9146)	16.0875*** (1.2660)
<i>Cost (scale)</i>	2.1776*** (0.0670)	-0.5728*** (0.0783)	-0.1678*** (0.0453)	1.0708*** (0.0702)
Model diagnostics				
Log-likelihood (constant only)	-16,153.2757			
Log-likelihood	-11,277.3470			
McFadden’s pseudo R ²	0.3019			
AIC/n	1.1091			
<i>n</i> (observations)	20,400			
<i>k</i> (parameters)	35			

Note: *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Table 4. Simulated marginal willingness-to-pay (PLN per year) associated with *signaled consequentiality* levels [95% confidence interval]

	<i>Status quo</i>	<i>Entertainment theatres</i>	<i>Drama theatres</i>	<i>Children's theatres</i>	<i>Experimental theatres</i>
<i>Signaled consequentiality</i> = 1	1.13 [-3.64, 5.94]	27.19 [23.32, 31.05]	16.18 [12.99, 19.39]	9.87 [6.85, 12.88]	9.90 [7.02, 12.81]
<i>Signaled consequentiality</i> = 2	2.06 [-1.32, 5.46]	30.72 [28.08, 33.37]	19.27 [17.14, 21.42]	10.30 [8.26, 12.31]	9.80 [7.83, 11.78]
<i>Signaled consequentiality</i> = 3	3.00 [-0.53, 6.48]	34.25 [31.50, 36.99]	22.36 [20.12, 24.59]	10.72 [8.60, 12.84]	9.69 [7.58, 11.81]
<i>Signaled consequentiality</i> = 4	3.93 [-1.12, 8.93]	37.78 [33.71, 41.84]	25.45 [22.03, 28.86]	11.15 [7.95, 14.35]	9.59 [6.42, 12.77]

Table 5. Simulated marginal willingness-to-pay (PLN per year) associated with *latent consequentiality* [95% confidence interval]

	<i>Status quo</i>	<i>Entertainment theatres</i>	<i>Drama theatres</i>	<i>Children's theatres</i>	<i>Experimental theatres</i>
<i>2.5th percentile</i>	14.61 [6.98, 22.37]	-32.07 [-40.85, -23.57]	-16.07 [-22.50, -9.82]	0.15 [-5.62, 5.89]	-11.41 [-17.33, -5.57]
<i>25th percentile</i>	6.71 [2.94, 10.51]	10.29 [6.34, 14.16]	8.15 [5.33, 10.93]	6.94 [4.39, 9.49]	2.45 [-0.10, 4.99]
<i>50th percentile</i>	2.56 [-0.67, 5.78]	32.55 [29.79, 35.31]	20.88 [18.76, 23.00]	10.52 [8.59, 12.43]	9.74 [7.81, 11.67]
<i>75th percentile</i>	-1.60 [-6.06, 2.84]	54.82 [51.19, 58.50]	33.61 [30.54, 36.73]	14.09 [11.19, 16.99]	17.03 [14.04, 20.01]
<i>97.5th percentile</i>	-9.52 [-18.16, -0.88]	97.30 [89.10, 105.81]	57.90 [51.25, 64.74]	20.91 [14.72, 27.14]	30.94 [24.50, 37.43]

Table 6. Simulated marginal willingness-to-pay (PLN per year) associated with *stated consequentiality* levels [95% confidence interval]

	<i>Status quo</i>	<i>Entertainment theatres</i>	<i>Drama theatres</i>	<i>Children's theatres</i>	<i>Experimental theatres</i>
<i>Stated consequentiality</i> = 1	58.94 [24.33, 94.09]	-269.67 [-308.58, -232.10]	-151.94 [-181.53, -123.28]	-38.00 [-64.50, -11.75]	-89.20 [-116.71, -62.12]
<i>Stated consequentiality</i> = 2	43.56 [18.46, 69.13]	-187.25 [-215.56, -159.85]	-104.80 [-126.13, -84.13]	-24.76 [-43.97, -5.72]	-62.22 [-82.13, -42.57]
<i>Stated consequentiality</i> = 3	4.52 [0.74, 8.48]	22.04 [11.50, 32.47]	14.87 [8.72, 20.94]	8.84 [6.18, 11.32]	6.29 [2.37, 10.04]
<i>Stated consequentiality</i> = 4	-36.17 [-61.28, -11.28]	240.15 [214.43, 266.92]	139.56 [120.07, 159.56]	43.85 [25.36, 62.55]	77.69 [58.61, 97.06]
<i>Stated consequentiality</i> = 5	-53.19 [-88.89, -17.71]	331.38 [294.23, 370.26]	191.71 [163.72, 220.46]	58.49 [32.06, 85.20]	107.56 [80.27, 135.34]

Table 7. Cross-tabulation of *signaled* versus *stated consequentiality* – number of cases

		<i>Stated consequentiality</i>					
		1	2	3	4	5	Total
<i>Signaled consequentiality</i>	1	21	70	204	103	21	419
	2	24	75	207	87	26	419
	3	24	75	200	92	25	416
	4	25	83	231	80	27	446
	Total	94	303	842	362	99	1700

	Alternative A	Alternative B (continuation of the current policy)
Entertainment theatres	No change	No change
Drama repertory theatres	Tickets for 5 PLN	No change
Children's theatres	No change	No change
Experimental theatres	Tickets for 5 PLN	No change
Annual cost for You	100 PLN	0 PLN
Your choice	☐	☐

Figure 1. An example choice set (translated from Polish)

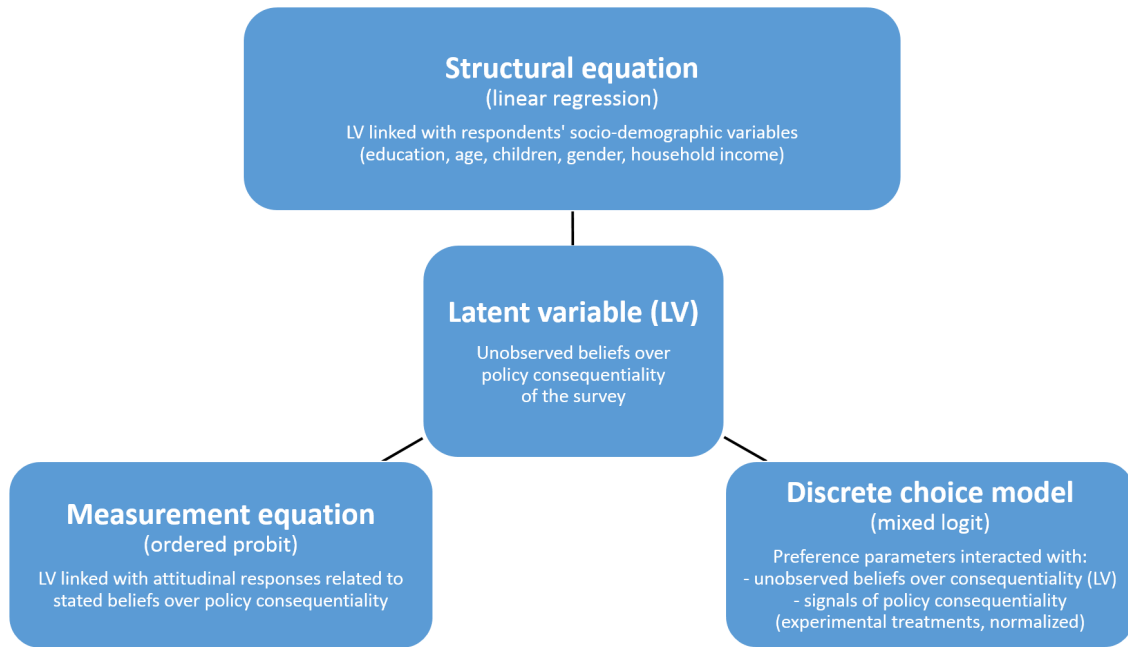


Figure 2. The HMXL model framework used to model the link between *signaled consequentiality* (information treatments), *stated consequentiality* (stated beliefs over consequentiality), respondents' socio-demographics and their stated preferences

Appendix. Additional estimation results

Table A1. Estimation results of the HMXL model investigating the role of consequentiality – the specification with the levels of *signaled consequentiality* entering as independent interactions

Structural equation (linear regression)						
dependent variable: <i>latent consequentiality</i>						
	Coefficient (s.e.)					
<i>Edu2</i>	0.1597* (0.0865)					
<i>Edu3</i>	0.0106 (0.0883)					
<i>Age</i>	-0.0044** (0.0019)					
<i>Children</i>	-0.0314 (0.0438)					
<i>Female</i>	0.2747*** (0.0621)					
<i>HH income</i>	0.1174*** (0.0303)					
Measurement equation (ordered probit)						
dependent variable: <i>stated consequentiality</i>						
	Coefficient (s.e.)					
<i>Latent consequentiality</i>	0.1765*** (0.0358)					
Threshold parameters:						
α_1	-1.6191*** (0.0514)					
α_2	-0.7381** (0.3534)					
α_3	0.6191* (0.3530)					
α_4	1.5944*** (0.3532)					
Willingness-to-pay model (mixed logit)						
	Means – main effects	Means – interactions with LV	Means – interactions with <i>signaled consequentiality</i> = 2	Means – interactions with <i>signaled consequentiality</i> = 3	Means – interactions with <i>signaled consequentiality</i> = 4	Standard deviations
	Coefficient (s.e.)	Coefficient (s.e.)	Coefficient (s.e.)	Coefficient (s.e.)	Coefficient (s.e.)	Coefficient (s.e.)
<i>Status quo</i>	-4.3918 (2.5256)	-6.3422*** (1.8742)	9.0878** (3.7474)	4.9330 (3.6708)	9.4414** (3.8387)	42.0438*** (1.3873)
<i>Entertainment theatres</i>	29.1927*** (2.2898)	33.3378*** (1.5225)	0.2440 (3.2658)	5.1762 (3.3302)	7.8938** (3.3142)	0.9735 (4.3048)
<i>Drama theatres</i>	16.6257*** (1.9650)	18.0429*** (1.4599)	2.8268 (2.7756)	5.8712** (2.7892)	7.7785*** (2.8208)	12.5953*** (1.4853)
<i>Children's theatres</i>	11.9430*** (1.7802)	4.8447*** (1.4292)	-3.6655 (2.5695)	-2.6607 (2.6263)	0.4987 (2.6489)	16.4436*** (1.2518)

<i>Experimental theatres</i>	9.1486*** (1.7612)	10.6719*** (1.4894)	1.5501 (2.5840)	2.5788 (2.7073)	-1.0695 (2.5590)	15.9873*** (1.2299)
<i>Cost (scale)</i>	2.4218*** (0.1119)	-0.5655*** (0.0780)	-0.1618 (0.1320)	-0.3132** (0.1321)	-0.4110*** (0.1278)	1.0871*** (0.0708)

Model diagnostics

Log-likelihood (constant only)	-16,153.2757
Log-likelihood	-11,271.6877
McFadden's pseudo R ²	0.3022
AIC/ <i>n</i>	1.1097
<i>n</i> (observations)	20,400
<i>k</i> (parameters)	47

Note: *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A2. Estimation results of the HMXL model investigating the role of consequentiality: *signaled consequentiality* included in the structural equation

Structural equation (linear regression)			
dependent variable: <i>latent consequentiality</i>			
	Coefficient (s.e.)		
<i>Signaled consequentiality</i>	0.0932*** (0.0322)		
<i>Edu2</i>	0.1131 (0.0946)		
<i>Edu3</i>	-0.0134 (0.0963)		
<i>Age</i>	-0.0036* (0.0021)		
<i>Children</i>	-0.0280 (0.0470)		
<i>Female</i>	0.3356*** (0.0655)		
<i>HH income</i>	0.0984*** (0.0317)		
Measurement equation (ordered probit)			
dependent variable: <i>stated consequentiality</i>			
	Coefficient (s.e.)		
<i>Latent consequentiality</i>	0.1536*** (0.0360)		
Threshold parameters:			
α_1	-1.6154*** (0.0510)		
α_2	-0.7371*** (0.0459)		
α_3	0.6154*** (0.0494)		
α_4	1.5873*** (0.0573)		
Willingness-to-pay model (mixed logit)			
	Means – main effects	Means – interactions with <i>latent consequentiality</i>	Standard deviations
	Coefficient (s.e.)	Coefficient (s.e.)	Coefficient (s.e.)
<i>Status quo</i>	2.2583 (1.6823)	0.2953 (2.0678)	46.4929*** (1.5207)
<i>Entertainment theatres</i>	33.8586*** (1.2280)	31.1932*** (1.4390)	1.0778 (4.7693)
<i>Drama theatres</i>	21.8204*** (1.0289)	18.5912*** (1.3492)	10.0314*** (1.7282)
<i>Children's theatres</i>	10.9018*** (0.9752)	4.3030*** (1.3883)	16.2181*** (1.2764)
<i>Experimental theatres</i>	10.2721*** (0.9717)	10.0178*** (1.4006)	15.8670*** (1.2901)
<i>Cost (scale)</i>	2.1581*** (0.0650)	-0.6213*** (0.0781)	1.0294*** (0.0685)
Model diagnostics			

Log-likelihood (constant only)	-16,153.2757
Log-likelihood	-11,281.1965
McFadden's pseudo R ²	0.3016
AIC/ <i>n</i>	1.1089
<i>n</i> (observations)	20,400
<i>k</i> (parameters)	30

Note: *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A3. Estimation results of the HMXL model investigating the role of consequentiality: *signaled consequentiality* included as indicators in the structural equation

Structural equation (linear regression)			
dependent variable: <i>latent consequentiality</i>			
	Coefficient (s.e.)		
<i>Information treatment T2</i>	0.0275 (0.0943)		
<i>Information treatment T3</i>	0.1673* (0.0909)		
<i>Information treatment T4</i>	0.2482*** (0.0908)		
<i>Edu2</i>	0.1581 (0.0951)		
<i>Edu3</i>	0.0257 (0.0967)		
<i>Age</i>	-0.0037 (0.0021)		
<i>Children</i>	-0.0436 (0.0477)		
<i>Female</i>	0.3648*** (0.0659)		
<i>HH income</i>	0.0940*** (0.0305)		
Measurement equation (ordered probit)			
dependent variable: <i>stated consequentiality</i>			
	Coefficient (s.e.)		
<i>Latent consequentiality</i>	0.1523*** (0.0360)		
Threshold parameters:			
α_1	-1.6148*** (0.0510)		
α_2	-0.7366*** (0.0362)		
α_3	0.6155*** (0.0461)		
α_4	1.5871*** (0.0502)		
Willingness-to-pay model (mixed logit)			
	Means – main effects	Means – interactions with <i>latent consequentiality</i>	Standard deviations
	Coefficient (s.e.)	Coefficient (s.e.)	Coefficient (s.e.)
<i>Status quo</i>	2.4773 (1.7203)	-0.0837 (2.1266)	46.4445*** (1.5277)
<i>Entertainment theatres</i>	33.6896*** (1.2452)	30.3515*** (1.5958)	4.3317 (4.6216)
<i>Drama theatres</i>	22.1581*** (1.0175)	20.4408*** (1.2508)	0.0000 (2.2986)
<i>Children's theatres</i>	10.8878*** (0.9867)	4.2671*** (1.3849)	16.5239*** (1.2529)
<i>Experimental theatres</i>	10.0500*** (0.9698)	9.6496*** (1.3563)	15.5905*** (1.2799)

<i>Cost (scale)</i>	2.1138*** (0.0599)	-0.6114*** (0.0741)	0.9988*** (0.0640)
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Model diagnostics

Log-likelihood (constant only)	-16,153.2757
Log-likelihood	-11,283.1342
McFadden's pseudo R ²	0.3015
AIC/ <i>n</i>	1.1093
<i>n</i> (observations)	20,400
<i>k</i> (parameters)	30

Note: *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A4. Estimation results of the HMXL model investigating the role of consequentiality: the measurement equation includes *signaled consequentiality*

Structural equation (linear regression)				
dependent variable: <i>latent consequentiality</i>				
	Coefficient (s.e.)			
<i>Edu2</i>	0.1533*		(0.0895)	
<i>Edu3</i>	-0.0297		(0.0896)	
<i>Age</i>	-0.0037**		(0.0019)	
<i>Children</i>	0.0143		(0.0444)	
<i>Female</i>	0.2983***		(0.0616)	
<i>HH income</i>	0.1271***		(0.0312)	
Measurement equation (ordered probit)				
dependent variable: <i>stated consequentiality</i>				
	Coefficient (s.e.)			
<i>Latent consequentiality</i>	0.1756***		(0.0361)	
<i>Signaled consequentiality</i>	-0.0280		(0.0268)	
Threshold parameters:				
α_1	-1.6178***		(0.0512)	
α_2	-0.7368***		(0.0409)	
α_3	0.6210***		(0.0448)	
α_4	1.5962***		(0.0546)	
Willingness-to-pay model (mixed logit)				
	Means – main effects	Means – interactions with <i>latent consequentiality</i>	Means – interactions with <i>signaled consequentiality</i>	Standard deviations
	Coefficient (s.e.)	Coefficient (s.e.)	Coefficient (s.e.)	Coefficient (s.e.)
<i>Status quo</i>	2.5599 (1.6413)	-6.1424*** (1.9457)	1.0251 (1.4203)	43.7656*** (1.5128)
<i>Entertainment theatres</i>	32.5523*** (1.2757)	32.9325*** (1.8297)	3.8912*** (1.1911)	5.4469 (4.4032)
<i>Drama theatres</i>	20.8831*** (1.0269)	18.8018*** (1.4950)	3.4236*** (1.0081)	11.6549*** (1.6126)
<i>Children's theatres</i>	10.5136*** (0.9684)	5.2878*** (1.4570)	0.4583 (0.9426)	15.3768*** (1.2716)
<i>Experimental theatres</i>	9.7428*** (0.9639)	10.7702*** (1.4887)	-0.1386 (0.9181)	16.0880*** (1.2646)
<i>Cost (scale)</i>	2.1776*** (0.0669)	-0.5727*** (0.0783)	-0.1661*** (0.0455)	1.0703*** (0.0702)

Model diagnostics	
Log-likelihood (constant only)	-16,153.2757
Log-likelihood	-11,276.7702
McFadden's pseudo R ²	0.3019
AIC/ <i>n</i>	1.1091
<i>n</i> (observations)	20,400
<i>k</i> (parameters)	36

Note: *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A5. Estimation results of the HMXL model investigating the role of consequentiality: the measurement equation includes indicators for *signaled consequentiality*

Structural equation (linear regression)				
dependent variable: <i>latent consequentiality</i>				
	Coefficient (s.e.)			
<i>Edu2</i>	0.1533* (0.0896)			
<i>Edu3</i>	-0.0296 (0.0897)			
<i>Age</i>	-0.0037** (0.0019)			
<i>Children</i>	0.0143 (0.0444)			
<i>Female</i>	0.2983*** (0.0616)			
<i>HH income</i>	0.1271*** (0.0313)			
Measurement equation (ordered probit)				
dependent variable: <i>stated consequentiality</i>				
	Coefficient (s.e.)			
<i>Latent consequentiality</i>	0.1754*** (0.0362)			
<i>Information treatment T2</i>	-0.0402 (0.0748)			
<i>Information treatment T3</i>	-0.0339 (0.0751)			
<i>Information treatment T4</i>	-0.0844 (0.0753)			
Threshold parameters:				
α_1	-1.6582*** (0.0699)			
α_2	-0.7772*** (0.0367)			
α_3	0.5807*** (0.0411)			
α_4	1.5560*** (0.0441)			
Willingness-to-pay model (mixed logit)				
	Means – main effects	Means – interactions with <i>latent consequentiality</i>	Means – interactions with <i>signaled consequentiality</i>	Standard deviations
	Coefficient (s.e.)	Coefficient (s.e.)	Coefficient (s.e.)	Coefficient (s.e.)
<i>Status quo</i>	2.5586 (1.6408)	-6.1436*** (1.9454)	1.0248 (1.4201)	43.7642*** (1.5128)
<i>Entertainment theatres</i>	32.5523*** (1.2735)	32.9326*** (1.8294)	3.8907*** (1.1907)	5.4463 (4.4017)
<i>Drama theatres</i>	20.8829*** (1.0264)	18.8013*** (1.4938)	3.4234*** (1.0075)	11.6558*** (1.6122)
<i>Children's theatres</i>	10.5137*** (0.9680)	5.2877*** (1.4567)	0.4585 (0.9424)	15.3770*** (1.2715)

<i>Experimental</i>	9.7423***	10.7699***	-0.1389	16.0881***
<i>theatres</i>	(0.9638)	(1.4878)	(0.9181)	(1.2642)
<i>Cost (scale)</i>	2.1776***	-0.5729***	-0.1661***	1.0703***
	(0.0670)	(0.0785)	(0.0455)	(0.0702)

Model diagnostics

Log-likelihood (constant only)	-16,153.2757
Log-likelihood	-11,276.6673
McFadden's pseudo R ²	0.3019
AIC/ <i>n</i>	1.1093
<i>n</i> (observations)	20,400
<i>k</i> (parameters)	38

Note: *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.

Table A6. Estimation results of the HMXL model investigating the role of consequentiality: socio-demographic explanatory variables removed from the structural component

Measurement equation (ordered probit) dependent variable: <i>stated consequentiality</i>				
	Coefficient (s.e.)			
<i>Latent consequentiality</i>	0.1682*** (0.0365)			
Threshold parameters:				
α_1	-1.6166*** (0.0509)			
α_2	-0.7367*** (0.0186)			
α_3	0.6190*** (0.0213)			
α_4	1.5927*** (0.0221)			
Willingness-to-pay model (mixed logit)				
	Means – main effects	Means – interactions with <i>latent consequentiality</i>	Means – interactions with <i>signaled consequentiality</i>	Standard deviations
	Coefficient (s.e.)	Coefficient (s.e.)	Coefficient (s.e.)	Coefficient (s.e.)
<i>Status quo</i>	2.2783 (1.5986)	-4.5405** (2.0360)	0.9861 (1.4260)	43.7046*** (1.5343)
<i>Entertainment theatres</i>	32.8046*** (1.2645)	31.7943*** (1.7345)	3.5086*** (1.1907)	6.7082 (3.6318)
<i>Drama theatres</i>	21.2209*** (1.0504)	18.1523*** (1.4493)	3.3342*** (0.9950)	12.8233*** (1.5369)
<i>Children's theatres</i>	10.5802*** (0.9674)	4.4299*** (1.4324)	0.3961 (0.9358)	16.3585*** (1.2819)
<i>Experimental theatres</i>	9.6359*** (0.9688)	10.4843*** (1.5006)	-0.0602 (0.9084)	16.7136*** (1.2467)
<i>Cost (scale)</i>	2.1956*** (0.0667)	-0.5608*** (0.0805)	-0.1620*** (0.0454)	1.0669*** (0.0705)
Model diagnostics				
Log-likelihood (constant only)	-16,153.2757			
Log-likelihood	-11,295.7580			
McFadden's pseudo R ²	0.3007			
AIC/ <i>n</i>	1.1103			
<i>n</i> (observations)	20,400			
<i>k</i> (parameters)	29			

Note: *, **, *** denote significance at the 10%, 5% and 1% levels, respectively.



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