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A fixed effects ordered choice model with flexible thresholds with an application to life-satisfaction

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Abstract

In many contexts reported outcomes in a rating scale are modeled through the existence of a latent variable that separates the categories through thresholds. The literature has not been able to separate the effect of a variable on the latent variable from its effect on threshold parameters. We propose a model which incorporates (1) individual fixed effects on the latent variable, (2) individual fixed effects on the thresholds and (3) threshold shifts across time depending on observables. Importantly, the latent variable and the threshold specifications can include common variables. In order to illustrate the estimator, we apply it to a model of life satisfaction using the GSOEP dataset. We demonstrate that important differences can arise depending on the choice of the model. Our model suggests that threshold shifts are statistically and quantitatively important. Factors which increase reported life-satisfaction are due both to positive effects on the latent variable AND to shifting thresholds to the left, while factors which decrease reported life satisfaction are due to negative effects on the latent variable AND to shifting thresholds to the right.

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1 Introduction

Many variables and outcomes of interest in the social sciences are reported in rating scales. Some of these separate the categories along pre-specified thresholds, such as categorical grades in school (A to E, 10 to 1, etc.), but many others do not. Surveyed individuals are often asked about their opinion on a certain statement or political issue with answer categories ranging from "Strongly agree" to "strongly disagree", their self-assessed health or well-being on a range from 0 to 10, or 1 to 5, how much they value certain things in life, such as family, friends, work, etc. with answers ranging from "very much" to "not at all", or how they assess their proficiency in a certain skill or task, such as language fluency with answers ranging from "very well" to "not at all". These rating scales are in wide use in disciplines as diverse as economics, psychology, and medicine (in rating the severity of pain, for example).

The ordinal (non-cardinal) nature of these variables has given rise to models of ordered choice such as the ordered probit and ordered logit models, and recent contributions have developed consistent and/or efficient (in the sense of using all sample observations with variation in the dependent variable) estimators for the ordered logit, which are all based on a dichotomization of the dependent variable and the application of Chamberlain's (1980) conditional logit model (Winkelmann and Winkelmann (1998), Das and van Soest (1999), Hamermesh (2001), Ferrer-i-Carbonell and Frijters (2004), Baetschmann et al. (2015)). All of these applications have assumed that the thresholds that divide one category from the other are fixed over time (but not necessarily across individuals). This is due to the fact that in ordered choice models the effect of a variable on the level of the latent variable cannot be separately identified from the variable's effect on the level of the thresholds. We suspect that researchers have been long aware of this, but the first explicit exposition of this problem goes back to Terza (1985). If thresholds do change systematically with observed variables, then the coefficient estimates in the aforementioned papers are not effects on the level of the latent variable, but rather on the level change of the latent variable *relative* to threshold locations (which might have changed themselves), and thus contain very little information, since even the sign cannot be interpreted in its effect on the latent variable.

We propose a model which can identify effects of variables on the latent variable from effects on the thresholds. To our knowledge this is the first paper which does this in the absence of objective measures of the latent variable (as done by Lindeboom and van Doorslaer (2004) for health) or of explicit anchoring vignettes (such as Bago d'Uva et al. (2011)). We use the Amalgamated Conditional Logit Regression (ACLR) proposed by Mukherjee et al. (2008)[3] and extend it by including dependent variables which reflect the survey individuals' answers to questions about their current outcome, but also their answers relating to the previous survey period's outcome. The latter is NOT the lagged dependent variable. Rather it is the individual's assessment today about her outcome last year. We illustrate our model by applying it to the outcome of life-satisfaction in the German Socio-Economic Panel. The application suggests that threshold shifts are statistically and quantitatively important. For example, about a third of the coefficient on household income in a model with fixed thresholds can in fact be attributed to a shift in thresholds.

Whether a change in the reported outcome is due to a change in the underlying latent variable or due to a change in the threshold might at first seem like an arcane question, but the inference, implications, and possibly political consequences can be widely different between the two cases. Consider first a simple example: In the British higher education system a grade of at least 70 (out of 100) is considered a "first class" grade. Conceivably, a first class graduation grade might be considered a necessary condition for a popular and attractive employer to consider an applicant for a job interview. Now suppose the proportion of "first class" grades increases over time. Since the threshold is fixed, one would be inclined to infer that students seem to be getting "better" in some sense, but that is so only if we interpret the latent variable as the actual grade (a number between

[3]Baetschmann et al. (2015) call this estimator "blow-up and cluster" (BUC) and demonstrate its strong small sample properties in Monte-Carlo simulations.

0 and 100). However, the result might be due to the university becoming more generous in its marking, so that a particular student might receive 70 marks today, but would have received less for the same performance a few years earlier. If we interpret the latent variable as "knowledge" or "quality of knowledge", then the increased proportion of first class grades could be a reflection of either more knowledgeable students, or as a laxation of marking standards. Clearly the distinction would be of interest to educational policy-making.

Another increasingly important field in which the distinction between latent variable and threshold changes is crucial is the measurement and study of subjective well-being and happiness. Measures of well-being are increasingly suggested as substitute or at least complementary measures to GDP that should be targeted by governments (see for example HM Treasury Budget (2010), OECD (2011) or Dolan et al. (2011)). Since these measures reflect the entirety of the human experience, it is argued, they have the potential to be more complete and even accurate compared to GDP which includes only those goods which can be priced in the market (thus excluding things like the value of clean air, social and physical safety, biodiversity etc.). A non-market good x could in principle be "priced" by inferring from regression coefficients the amount of income that an individual would give up to compensate for a unit-increase in x to keep her latent variable constant.[4] But what exactly should the social welfare function be? If it is the sum of all individual reported levels of well-being ($Y = \sum_{i=1}^{N} y_i$), we need not worry about the source of changing values of y, since both threshold and latent variable changes will be observationally equivalent. But if the social welfare function is over the latent variable ($Y^* = \sum_{i=1}^{N} y_i^*$), as it probably should be if we consider this to be the actual emotional state of an individual, then the distinction is important. Threshold shifts to the left (making it easier to report higher values of well-being) would increase Y, but leave Y^* unchanged. We imagine a policy-maker would like to know to what extent changes in Y are reflecting changes in Y^*.

[4] It is not our intention to participate in a debate about the merits of using well-being instead or along with GDP. We only illustrate that threshold shifts can occur and will have different implications from latent variable shifts.

2 Modeling

We follow here the conventional choice of setting up the ordinal model as a latent variable model. That is the individual i at any given point of time t has a subjective evaluation of the question she is being asked (her health status, opinion, life-satisfaction, etc.). The question can only be answered by picking one out of an ordered list of answers. We index the possible answer categories by $k \in \{1, ...K\}$. The individual's evaluation of her underlying latent variable we denote y_{it}^*. This evaluation translates into the reported outcome y_{it}, such that

$$y_{it} = k \quad \Leftrightarrow \quad \lambda_{it}^{k-1} < y_{it}^* \leq \lambda_{it}^k \tag{1}$$

The latent variable is specified as

$$y_{it}^* = X_{it}\beta + \alpha_i + \epsilon_{it} \tag{2}$$

where the distribution of α_i is left unspecified and is allowed to correlate with X_i, and ϵ_{it} is i.i.d. logistic (with location 0 and scale 1) across i and t.

2.1 Threshold model

If $\lambda_{it}^k = \lambda_i^k$, we have all the necessary building blocks to apply Chamberlain's conditional logit model for a pre-specified dichotomization of y, or to apply one of the estimators based on the conditional logit model which use all possible dichotomizations (minimum distance, ACLR). This specification of the threshold parameters is quite flexible, but it does impose that distances between any two thresholds are preserved over time, or

$$\lambda_{it}^k = \lambda_{i,t-s}^k$$

and that the difference of the k$^{\text{th}}$ threshold between two individuals is constant over time:

$$\lambda_{it}^k - \lambda_{jt}^k = \lambda_i^k - \lambda_j^k$$

It also implies that $y_{it} > y_{is} \Rightarrow y_{it}^* > y_{is}^*$.

In this paper we decompose the thresholds into an individual- and threshold-specific, time-invariant component, and a component which modifies the thresholds linearly in parameters:

$$\lambda_{it}^k = \tau_i^k + Z_{it}\gamma \tag{3}$$

Thus,

$$\lambda_{it}^k - \lambda_{jt}^k = \tau_i^k - \tau_j^k + (Z_{it} - Z_{jt})\gamma$$

and $y_{it} > y_{is}$ does not necessarily imply $y_{it}^* > y_{is}^*$. Equations 1, 2 and 3 imply

$$y_{it} = k \quad \Leftrightarrow \quad \tau_i^{k-1} < X_{it}\beta - Z_{it}\gamma + \alpha_i + \epsilon_{it} \leq \tau_i^k \tag{4}$$

Clearly, in this equation β is not separately identified from γ for common variables in X and Z, or in other words, the estimate of β will incur a level-bias on the order of $-\gamma$.

2.2 The remembered outcome

In most surveys the surveyed individual is asked to rate her current outcome. However, the surveyed individual might in addition be asked about the current outcome and about her outcome at some point in the past. In that case we need to distinguish between the *survey time*, which we will be subscripting, and the *reference time*, which we will be superscripting. Thus, y_{it}^t is the reported outcome for individual i surveyed at time t and where the evaluation refers to the time at which the individual is surveyed. In contrast y_{it}^{t-1} is the reported outcome for individual i surveyed at time t but where the evaluation refers to the *previous* time at which the individual is surveyed: it is how the individual remembers her outcome. Assuming the individual to have an accurate recollection of her previous outcome, and having time-invariant thresholds, a difference between y_{it}^t and y_{it}^{t-1} would be due to a change in the individual's latent variable. Our threshold specification also allows this to be due to changes in the threshold parameters – provided that the thresholds of time t are applied to all questions at survey time t. A prominent example would be the effect of income or wealth on an outcome variable which records the individual's assessment about how rich he or she is: the barrier that divides the rich from the non-rich always seems to be above one's own wealth. A third possibility would be that the individual does not accurately recall her previous state. We assume that the *remembered* latent variable at survey time t is the *non-random component* of the latent variable at reference time $t-1$ amended by an additive recall error u_{it}. Since the error in the latent variable ϵ_{it} is assumed to be identically and independently (of X) distributed, one can interpret it as a merely transitory component that influences the reported answer at the time of the survey (the "mood" of the surveyed person). Thus, we assume that the individual does remember her circumstances of the previous survey time (as reflected in the X), but not the purely transitory aspect that contributed to her answer on that day. The recall error u_{it} can be interpreted as both a false recollection and/or as a discrepancy between the points of time in a past time period (the surveyed individual questioned about her outcome "last year" might not refer to the point of time at which she was surveyed in the previous year). We write:

$$y_{it}^{t-1} = k \quad \Leftrightarrow \quad \lambda_{it}^{k-1} < y_{i,t-1}^{*} - \epsilon_{i,t-1} + u_{it} = X_{i,t-1}\beta + u_{it} \leq \lambda_{it}^{k}$$

This, together with equations 2 and 3 give

$$y_{it}^{t-1} = k \quad \Leftrightarrow \quad \tau_{i}^{k-1} < X_{i,t-1}\beta - Z_{it}\gamma + \alpha_i + u_{it} \leq \tau_{i}^{k} \tag{5}$$

This is the equation which identifies β and γ separately, even if X and Z share common variables, since the variables in X enter with a one-period lag compared to Z.

We emphasize that this derives from the application of thresholds λ_{it} rather than $\lambda_{i,t-1}$ to ANY question asked at survey time t. We think that for most cases it is reasonable to assume that people apply their current criteria in answering a survey question, even if the question refers to an event in the past. We make the following assumption on u_{it}:

- The **recollection error** u_{it} is distributed i.i.d. and follows a logistic distribution with location 0 and scale σ. It is unrelated to observables X_{it} and Z_{it}, so that $COV(u_{it}, X_{it}) = COV(u_{it}, Z_{it}) = 0$.

An important point to bear in mind is that the model with time-invariant thresholds would be observationally equivalent *with regard to the current reported variable* y_t^t to the model with threshold shifts. Thus we cannot base a discriminating test on the variable y_t^t. This is a consequence of the model with time-invariant thresholds not having a specification – a "theory" – for categorical outcomes referring to the past. We therefore also estimate an alternative model based on both the current and the past reference period, but modify our model such that the thresholds an individual applies are always the thresholds of the reference period (rather than the survey period). That is, an individual reporting a value for y_i^{t-1} applies the thresholds $\lambda_{i,t-1}$ in categorizing his latent variable $y^*_{i,t-1}$. This model cannot identify between latent variable and threshold shifts, but it "predicts" the remembered outcomes. We can thus compare the likelihood values between this and our model.

3 Estimation

The estimation is a very straightforward extension of the estimator in Mukherjee et al. (2008), who call it amalgamated conditional logistic regression (ACLR) and Baetschmann et al. (2015)[5] who call it "blow up and cluster" (BUC) estimator. The idea of these estimators is the following: for a given cutoff value k, dichotomize the ordinal variable, e.g. $\tilde{y}_{it} = 1(y_{it} > k)$. Chamberlain's conditional logit model is derived from the likelihood of the sequence of $\tilde{y}_{it}$ conditional on $\sum_{t=1}^{T_i} \tilde{y}_{it}$. Denoting this by P_i^k, the ACLR and BUC combine all the possible dichotomization (with K categories, there are K-1 possible dichotomizations) in one log likelihood and maximize it over b

$$\max_b LL = \sum_{i=1}^{N} \sum_{k=1}^{K-1} \ln P_i^k(X, b) \tag{6}$$

Under the assumptions on ϵ_{it}, an individual's likelihood $P_i^k(X, b)$ is given by

$$P_i^k(X, b) = \frac{\prod_{t=1}^{T_i} \exp(\tilde{y}_{it} * X_{it}\beta)}{\sum_{d_i \in D_i} \prod_{t=1}^{T_i} \exp(d_{it} * X_{it}\beta)}$$

[5] We are very thankful to the authors for bringing these models to our attention and for providing the Stata code for implementation.

where $d_{it} \in \{0,1\}$, $d_i = (d_{i1} \cdots d_{iT_i})$ and D_i is the set of all distinct d_i such that $\sum_t d_{it} = \sum_t \tilde{y}_{it}$. Our extension to this model is the following. Suppose individual i has T_i^{pr} observations on y_{it}^t (where the superscript pr stands for present), and T_i^{pa} observations on y_{it}^{t-1} (past). We stack first the reported outcomes y_{it}^t for individual i and over all t, followed by y_{it}^{t-1} for individual i and over all t, these are the first $T_i^{pr} + T_i^{pa}$ elements of the outcome vector. The vector is then appended by the next individual etc. until we reach the end of our sample. Since the u_{it} are assumed to be independent of the ϵ_{it}, statistically we can treat the observations for y_{it}^{t-1} and y_{it}^t as distinct individuals even if in reality they are responses by the same individual. The vector for the explanatory variables are $(x_{it}, -z_{it})$ for responses referring to the present period, and $(x_{i,t-1}, -z_{it})$ for responses referring to the past period. With these modifications to the data, the likelihood given in 6 is maximized. Standard errors are clustered by distinct ϵ_{it} and u_{it}. We will be distinguishing four different models: ACLR is the model applied in Mukherjee et al. (2008), and Baetschmann et al. (2015). ACLR - A (for alternative) is the ACLR model which includes the outcomes y_{it}^{t-1} but applies thresholds $\lambda_{i,t-1}$ to this outcome. Our model is ACLR - T (for threshold) and ACLR - T with σ. Both models apply thresholds of the *survey* period to any outcome (y_{it}^t and y_{it}^{t-1}. ACLR - T fixes the scale parameter of the recollection error to 1, while ACLR - T with σ estimates this parameter jointly with the latent variable and threshold parameters. Due to its added flexibility in modeling the remembered outcome our preferred specification is ACLR - T with σ.

4 Application: Life satisfaction over the life cycle

We illustrate the working of our model by way of an application to life satisfaction. We use the German Socio-Economic Panel (GSOEP). This annual panel contains the question "How satisfied are you at present with your life as a whole?" in all waves (the first panel wave is 1984). For the waves 1984-1987 the GSOEP also asked the question "How satisfied were you a year ago with your life?" Both questions could be answered on a scale from 0 (totally satisfied) to 10 (totally unsatisfied). We restrict the sample to all individuals between ages 25 and 64, and after this sample selection, to observations who have non-missing values for all contemporaneous variables in all four years (missing values might still be present in the extended model for the lagged independent variable and for y_{it}^{t-1}). The balancing of the panel leads to a loss of 33% of individual-year observations. However, these include both attritions and additions due to reaching the age of 16 at which individuals are interviewed (see Haisken-DeNew and Frick (2005), p. 21).

Since equation 5 requires values on the lagged independent variables, we cannot use y_{it}^{t-1} for 1984. We thus have 3 answers to the question about last year's happiness and 4 answers to the question about current happiness. In principle more waves could be used for the latter. However, parameters need not stay stable over time, and we stop the sample two years before the fall of the Berlin wall and any structural break that might have accompanied it.

We model life-satisfaction very similarly to Baetschmann et al. (2015). The explanatory variables for the latent variable equation are: the log of household income (in 2010 Euros), age squared, a dummy for unemployment, a dummy for not being in the labor force, a dummy for living with a partner (married or not), a dummy for being in good health (defined as not suffering from a chronic illness and not having been hospitalized during the last year), and survey year dummies. To emphasize the main contribution of this paper, all of those variables except the year dummies are also included as threshold shifters.

We do not claim to have a complete model of life-satisfaction which would be outside of the scope of this paper. However, we think that the chosen variables cover most of the determinants of life satisfaction that have been considered in the literature (see for example Dolan et al. (2008)).

Before showing regression results, table 1 demonstrates the discrepancy in the outcome variables y_{t-1}^{t-1} (life satisfaction referring to t-1 as reported in t-1) and y_{t}^{t-1} (life satisfaction referring to t-1 as reported in t). A cell entry is the percentage of those who report y_{t}^{t-1}, conditional on reporting y_{t-1}^{t-1} (so the rows sum to 100). The diagonal elements would be the "consistent" answers. In period t, the plurality of observations record an answer consistent with the reported life satisfaction in $t-1$ only for categories 5 (26%), 7 (30%), 8 (37%) and 10 (37%). All off-diagonal elements have positive entries (except $y_t^{t-1} = 10 | y_{t-1}^{t-1} = 0$), and people seem to "revise" their life-satisfaction both upwards and downwards with a slight tendency for downwards revision: there are 5,675 observations in the lower and 4,196 observations in the upper triangle of the table. The observations in the diagonal cells are 4,202. This phenomenon lends strong support to the hypothesis of flexible thresholds and/or the presence of a recall error.

Table 1: **Cross-tabulations, Life satisfaction in %**

LS in t-1 as reported in t-1: y_{t-1}^{t-1}	Life satisfaction in t-1 as reported in t: y_t^{t-1}											
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Total obs**
0	12.7	4.2	9.3	18.6	12.7	19.5	8.5	6.8	5.9	1.7	0.0	118
1	6.6	8.2	16.4	11.5	8.2	14.8	11.5	4.9	13.1	3.3	1.6	61
2	4.3	4.3	8.6	12.3	12.3	29.6	9.9	5.6	8.0	2.5	2.5	162
3	4.1	2.4	6.1	12.3	14.7	23.5	12.6	11.3	8.5	2.7	1.7	293
4	1.9	1.1	6.3	13.4	10.4	25.7	16.9	12.0	8.5	2.7	1.1	366
5	1.3	0.6	2.3	4.9	9.0	26.9	15.7	16.5	14.8	4.3	3.8	1,667
6	0.6	0.2	1.4	4.0	7.3	17.8	17.9	24.8	17.7	4.9	3.4	1,313
7	0.2	0.1	0.7	1.4	2.9	13.2	14.6	29.6	26.6	7.2	3.6	2,471
8	0.2	0.2	0.5	0.9	1.6	7.8	8.6	23.4	37.4	13.0	6.4	3,777
9	0.1	0.1	0.3	0.7	0.8	4.5	5.4	15.2	33.4	28.4	11.2	1,814
10	0.3	0.1	0.4	0.5	1.0	4.7	4.1	9.6	23.6	18.7	36.9	2,034
Total	95	55	183	357	536	1,723	1,495	2,782	3,721	1,726	1,403	14,076

Source: German Socio-Economic Panel 1984-1987. LS: Life satisfaction.

Table 2 presents results for our life-satisfaction model for the full sample, and compares it to the ACLR estimator which is based on the current reported life-satisfaction only and to the alternative model ACLR - A as described above.

Table 2: Life satisfaction determinants - Full sample

	(1)	(2)	(3)	(4)
	ACLR	ACLR - A	ACLR - T	ACLR - T with σ
latent variable				
ln(household income)	0.275***	0.215***	0.173**	0.145
	(0.078)	(0.059)	(0.068)	
Unemployed	-0.926***	-0.840***	-0.724***	-0.632
	(0.119)	(0.092)	(0.108)	
Not in labor force	-0.199**	-0.152**	-0.123	-0.112
	(0.097)	(0.074)	(0.090)	
Healthy	0.344***	0.259***	0.126***	0.134
	(0.047)	(0.037)	(0.042)	
Has partner	0.536***	0.504***	0.204	0.223
	(0.154)	(0.117)	(0.155)	
Age squ.	0.061	0.041	-2.222	-3.574
	(0.073)	(0.060)	(1.535)	
threshold				ln(household income)
ln(household income)			-0.074	-0.073
			(0.069)	
Unemployed			0.219**	0.251
			(0.109)	
Not in labor force			0.041	0.037
			(0.094)	
Healthy			-0.260***	-0.237
			(0.042)	
Has partner			-0.422***	-0.366
			(0.153)	
Age squ.			-2.279	-3.631
			(1.535)	
σ				0.76

Source: SOEP 1984-1987. All regressions include survey year dummies for the latent variable. For columns (1) to (3) standard errors are clustered by individual and reported outcome (past vs. present). For column 4 standard errors are not yet available. *** p<0.01, ** p<0.05, * p<0.1.

Not surprisingly, the results for β in the ACLR model are roughly equal to $\beta - \gamma$ in the ACLR - T model. Minor differences are due to missing values (for example in y_{it}^{t-1}). As expected, we see that important factors for reported life-satisfaction are income, good health, and employment. The results suggest that accounting for threshold shifting variables can be quite important in practice. In our preferred model (column 4) a third of the apparent increase in life-satisfaction through income seems to be attributable to higher income shifting the threshold of what constitutes high levels of life-satisfaction to the left. We had admittedly expected the opposite effect. However, the results also seem to suggest that the factors which increase (decrease) reported life-satisfaction (in the ACLR model) have this dual effect: they increase (decrease) the latent variable in our model, but also shift the thresholds to the left (right). We see this phenomenon for all our variables except age. We don't want to read to much into such a parsimonious model, but a possible explanation is that the things that constitute a good life might seem to be more easily attainable to people who have it, while they might look distant and out of reach for those who lack it. Another important point is that the ACLR - T model performs better than the ACLR - A model in terms of the Pseudo R^2 value. In the full sample this goodness of fit measure is 13% higher for the ACLR - T than for the ACLR - A model. We view this finding as supporting the remembered outcome specification we have proposed in this paper.

We are also interested in how income, unemployment and marital status affect men and women differently and report results separated by sex in tables 3 and 4. Household income seems to have comparable effects on both men and women, though the effect on the latent variable – the emotional state – is smaller than the ACLR and ACLR - A models would suggest. An interesting difference exists with relation to employment status. Men are clearly much more negatively affected than women in their emotional state, while women seem to react to unemployment in part by shifting out their thresholds. Not being in the labor force has no effect on women, but affects men negatively. Presumably this is a life-style choice for women in that era, while for men non-participation might reflect hidden unemployment or the inability to work. We also observe that having a partner has a much stronger effect on thresholds than on the latent variable itself. Finally, aging decreases women's life-satisfaction strongly, but again women seem to "adapt" to this by changing the thresholds, and by finding it easier – for a given emotional state – to define this state as a relatively high level of life-satisfaction.

Important quantitative differences also exist in the implied compensating incomes of conditions like good or bad health or unemployment. We consider the dummy variables in our model in table 5. The "shadow prices" in the model with flexible thresholds (columns 2 and 4) are based on compensating incomes for incremental changes in the probability of switching from 0 to 1 in the variable of interest. The shadow prices are based on changes in income to keep the latent variable constant (rather than keeping the log odds-ratio constant). For example an increment of 1 percentage point in the probability of getting unemployed is compensated by an increase of 4.38% in the household income to keep the life-satisfaction of a man constant. In the ACLR model no distinction between the effect of a variable on the latent variable and the log odds-ratio can be made. We see that for some variables the two models can imply very different shadow prices. This is mostly clearly seen in the labor force variables, which according to our estimates have higher shadow prices than the conventional ACLR model would imply. The not-in-labor-force variable switches from positive to negative, though the difference between the two estimates is not statistically significant. Finally, while the ACLR model suggests that having a partner is more valuable for men than for women, this finding is reversed in our flexible threshold model.

5 Conclusion

It has been a long-standing insight that in ordered-choice models there is an observational equivalence between a variable's effect on the latent variable and on the threshold, and that only the combined effect is identified. However, in practice the difference between changes in the latent variable and the threshold can be important for inference and policy-making. We are proposing a model of ordered choice which accommodates the inclusion of 1) individual fixed effects in the latent variable, and 2) individual specific thresholds which are allowed to change through time.

Table 3: Life satisfaction determinants - Women

	(1)	(2)	(3)	(4)
	ACLR	ACLR - A	ACLR - T	ACLR - T with σ
latent variable				
ln(household income)	0.260**	0.188**	0.161*	0.098
	(0.109)	(0.084)	(0.095)	
Unemployed	-0.588***	-0.474***	-0.316**	-0.244
	(0.161)	(0.125)	(0.153)	
Not in labor force	-0.006	0.014	0.024	0.015
	(0.113)	(0.086)	(0.103)	
Healthy	0.318***	0.247***	0.111**	0.127
	(0.062)	(0.049)	(0.056)	
Has partner	0.424*	0.475***	0.225	0.224
	(0.233)	(0.176)	(0.227)	
Age squ.	0.169*	0.096	-2.222	-5.442
	(0.101)	(0.083)	(2.159)	
threshold				
ln(household income)			-0.048	-0.033
			(0.095)	
Unemployed			0.294*	0.248
			(0.158)	
Not in labor force			0.013	0.002
			(0.110)	
Healthy			-0.273***	-0.212
			(0.056)	
Has partner			-0.370*	-0.284
			(0.216)	
Age squ.			-2.336	-5.511
			(2.158)	
σ				0.54

Source: SOEP 1984-1987. All regressions include survey year dummies for the latent variable. For columns (1) to (3) standard errors are clustered by individual and reported outcome (past vs. present). For column 4 standard errors are not yet available. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Life satisfaction determinants - Men

	(1) ACLR	(2) ACLR - A	(3) ACLR - T	(4) ACLR - T with σ
latent variable				
ln(household income)	0.287**	0.229***	0.163*	0.162
	(0.113)	(0.084)	(0.098)	
Unemployed	-1.258***	-1.214***	-1.138***	-1.163
	(0.175)	(0.136)	(0.157)	
Not in labor force	-0.559***	-0.459***	-0.356*	-0.388
	(0.188)	(0.145)	(0.186)	
Healthy	0.365***	0.266***	0.136**	0.134
	(0.071)	(0.056)	(0.065)	
Has partner	0.604***	0.512***	0.161	0.171
	(0.205)	(0.156)	(0.210)	
Age squ.	-0.041	-0.005	-2.315	-2.114
	(0.106)	(0.089)	(2.182)	
threshold				
ln(household income)			-0.112	-0.111
			(0.101)	
Unemployed			0.143	0.126
			(0.151)	
Not in labor force			0.148	0.136
			(0.185)	
Healthy			-0.244***	-0.250
			(0.065)	
Has partner			-0.473**	-0.464
			(0.216)	
Age squ.			-2.329	-2.131
			(2.184)	
σ				1.03

Source: SOEP 1984-1987. All regressions include survey year dummies for the latent variable. For columns (1) to (3) standard errors are clustered by individual and reported outcome (past vs. present). For column 4 standard errors are not yet available. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Shadow prices

	Men		Women	
	ACLR	ACLR-T with σ	ACLR	ACLR-T with σ
Unemployed	4.38	7.16	2.27	2.50
Not working	1.95	2.39	0.02	-0.16
Healthy	-1.27	-0.83	-1.22	-1.30
Has partner	-2.10	-1.05	-1.63	-2.29

Source: SOEP 1984-1987.

Crucially, our model can incorporate the same variables for the latent variable and the threshold and identify their separate effects. We apply our estimator to a simple model on life satisfaction and demonstrate that variables usually included in life-satisfaction models have statistically and quantitatively significant effects on the thresholds, which if omitted in the threshold specification are absorbed in the coefficient of the latent variable specification. Quantitatively important differences in the values of variables like unemployment, having a partner, health and not being in the labor force arise between models with and without threshold shifts. Since our modeling strategy depends on the availability of retrospective information on the dependent variable, we hope that this paper will increase awareness for the importance of the inclusion of these variable in surveys.

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