I feel good! Gender differences and reporting heterogeneity in self-assessed health

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Gender differences and reporting heterogeneity in self-assessed health

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For empirical analysis and policy-oriented recommendation, the precise measurement of individual health or well-being is essential. The problem with variables based on questionnaires such as self-assessed health is that the answer may depend on individual reporting behaviour. Moreover, if individual's health perception varies with certain attitudes of the respondent reporting heterogeneity may lead to index or cut-point shifts of the health distribution, causing estimation problems. We analyse the reporting behaviour of individuals on their self-assessed health status, a five-point categorical variable. We explore observed heterogeneity in categorical variables and include unobserved individual heterogeneity using German panel data. Estimation results show different impacts of socioeconomic and health related variables on the five subscales of self-assessed health. Moreover, the answering behaviour varies between female and male respondents, pointing to gender specific perception and assessment of diseases. Reporting behaviour on self-assessed health questions in surveys is problematic due to a possible heterogeneity. Hence, in case of reporting heterogeneity, using self-assessed measures in empirical studies may be misleading or at least ambiguous.

JEL-Classification: I12, C21

Keywords: reporting heterogeneity, generalized ordered probit, self-assessed health

1. Introduction

The measurement of individual health or well-being is crucial in health economics. In many empirical studies, various measures like self-assessed health, satisfaction with health or health worries are used [1, 2]. Such indicators are common to data sets and help to compare the results of different studies. The problem with the use of such variables is that the answer depends on the one hand on the questionnaire or even on the interviewer and on the other hand on the individual perception of the question.

In the following, we concentrate on individual reporting behaviour and look for systematic differences between population subgroups. If the reporting behaviour is related to socioeconomic status, age, education or labour force status, different subgroups of the population report their health status differently. Problems arise if self-reported health that is used as explanatory variable is prawn to endogeneity problems. In the empirical analysis, we use data from the German SAVE study where multiple imputation methods are used to deal with item non-response. Besides a categorical measure of self-related health several questions about the individual experience with sever or chronic diseases are included and may serve as objective health status.

Individual answers are the basis to the question about self-assessed health status, a five-point categorical variable. We show that a simple ordered probit analysis neglects the fact that the classification into the five subscales depends on socioeconomic as well as health related variables. Moreover, the answers differ between female and male respondents. To take care of these problems, we use a generalized ordered probit estimation to cope with a possible heterogeneity in reporting behaviour and to identify possible sources of heterogeneity. This technique can be used to measure how reliably a person carries out health related items in a questionnaire.

The paper is organized as follows: Section two reviews the literature dealing with self-assessed health reporting heterogeneity. In the following chapter, we describe the dataset and discuss the relevant estimation techniques followed by the presentation of the results in chapter four. The last chapter summarizes the findings and discusses further research topics.

2. Literature review

The literature about the use and interpretation of health indicators like self-assessed health in empirical research is widespread. Among the first, Butler et al. [3] discuss a potential measurement error in self-reported health when studying work behaviour. They analyse the relationship between a dichotomous measure of self-reported health and a clinical indicator. The clinical indicator covered symptoms of arthritis while self-reported health is based on the question whether the respondent had arthritis or rheumatism. Empirical evidence shows that working individuals correctly report their health more likely. The same results are obtained for high school education and higher income. As a consequence, Butler et al. argue that traditional measures of self-reported health are valid indicators of actual health but have to be used in line with socioeconomic characteristics.

The difference between self-reported and objective measures of health like specific health conditions or limitations or doctor's reports for the retirement decision is analysed by Bound [4]. He follows that the problem of endogeneity and measurement error problems cannot be solved simultaneously. For his analysis, he uses self-reported health and one objective health measure. If the latter is not perfectly correlated with current health status the statistical model is not identified.

The impact of different health measures is analysed using the Retirement History Survey. When self-reported measures are used, health is more important than economic factors compared to the usage of more objective health measures. Moreover, both measures show a potential bias. As long as the objective proxies are not perfectly correlated with work capacity errors in variables problems occur that lead to a potential bias.

Kerkhofs and Lindeboom [5] analyse labour supply and retirement decisions and the influence of subjective health measures. A reporting error of the health measure may depend on the labour market status and self-reported health can be viewed as endogenous in labour supply and retirement models. In their analysis, they use an objectified subjective health measure that may be derived from questionnaires on various health problems or diseases. Using Dutch panel data, they estimate ordered response models that allow the thresholds to depend on labour market states and exogenous variables. The results suggest that individuals receiving disability allowance show large and systematic reporting errors. They conclude that subjective health measures therefore lead to biased estimates and conclusions. Using Canadian data, Baker et al. [6] find evidence that there exist substantial errors in measures of self-reported health. Moreover, these errors seem to be smaller for those in the labour force while they are larger if the assessment of health leaves room for subjective interpretation. Disney et al. [7] focus on retirement behaviour in Britain and the influence of ill health. They use self-assessed health as the predictor of health status and instrument this variable using an ordered probit model with health indicator variables and personal characteristics as explanatory variables. The predicted values of this model are then normalized and the resulting health stock enters the retirement equation to mitigate a possible endogeneity problem.

A review about the relationship between labour force status of older workers and health is presented by Lindeboom [8]. The important influence of health and financial incentives on the decision to retire is overshadowed by measurement problems and the fact that health and work are jointly determined. He discusses a framework for the interrelations between health and work focussing on the measurement of health. If both, subjective and objective indicators of health are only poor measures of that health status that is relevant for work-related decisions this will lead to a downward bias in the effects of health. For empirical models, Lindeboom and Kerkhofs [9] specify a model where the individual differences in reporting can be taken into account by an estimation strategy where the response thresholds of a model for ordered categories depend e.g. on the labour force status.

Income-related health inequality and reporting problems of self-assessed health are explored by van Doorslaer and Jones [10]. They argue that sub-groups of the population might use systematically different thresholds for classifying their health into a categorical measure even if the underlying true health is at the same level. The differences in the thresholds may be influenced by age, gender, education and individual experience with illness and the health care system. Van Doorslaer and Jones use the ‘Health Utility Index Mark III (HUI)’ to scale the responses to the self-assessed health question and compare different estimation techniques. They find that an interval regression approach outperforms other methods and should be used to measure and decompose health inequality. The same topic is analysed by Bago d’Uva et al. [11]. They find socio-economic differences in health reporting for Indonesia, India and China. Homogeneous reporting could be ruled out for all countries under review as well as a parallel shift of the reporting thresholds, implying that the assessment of the same health categories will differ between countries. Ziebarth [12] presents a comparison of different health measures in case of reporting heterogeneity and analyses their impact on an indicator of inequality (concentration index as a form of inequality measure). He finds that self-assessed health goes along with the highest degree of inequality. If alternatively a variable like doctor visits is used, the concentration index is significantly lower, i.e. it is reduced by the factor ten if the SF-12 health indicator is used. Summarizing, Ziebarth argues that income-related reporting heterogeneity is a complex problem in generic health measures.

Another strand of the literature [13] analyses the presence of cut-point and index shifts in self-reported health measures. Heterogeneous reporting behaviour means that different population sub-groups use different reference points when answering health related questions. Thereby, an index shift may occur if the reporting behaviour leads to a parallel shift of the thresholds while the relative position of the categories remains unchanged. With a cut-point shift, the thresholds are affected differently by the response behaviour. Lindeboom et al. find evidence for both kinds of shifts depending on age and gender but not on income, education or language skills.

Effects of different wordings in questionnaires and consequences of reporting bias and heterogeneity are studied by Hernández-Quevedo et al. [14]. They focus on the existence of index and cut-point shifts in the British Household Panel Survey. The change of the questionnaire in wave eight can be interpreted as a natural experiment. By applying ordered probit and generalized ordered probit models, they can show that there was an index shift in wave 9 but find no evidence for a cut-point shift due to the different wording in wave 9 questionnaire on self-reported health.

The dependence of reporting health on income is analysed by Etilé and Milcent [15]. They view self-assessed health as a biased measure of clinical health (the target outcome for public health policies). The link between income and health is analysed using two procedures: first, heterogeneous effects of income on the cut-points can be interpreted as reporting heterogeneity. Second, they use a proxy measure of clinical health to control for the income effect on clinical health. Any remaining impact on self-assessed health is then due to reporting heterogeneity.

With French data from 2001, the estimation results show that there is substantial income-related heterogeneity in self-assessed health.

From an international perspective, Juerges [16] explores the differences in true vs. reported health using data from the Survey of Health, Ageing and Retirement in Europe for the year 2004. For ten countries, he finds that self-reported health shows large cross-country differences. The variation could be reduced if self-reported health distributions are assumed to possess an underlying identical response style. This means that cross-country variation depends to a certain amount on the differences in reporting styles.

Our paper can be classified into the literature as follows: we analyse the reporting behaviour of individuals to questions on their self-assessed health status by estimating random effects generalized ordered probit models that allow deviating from the parallel regression assumption. In other words, the individual assessment "good or bad health" can be found to be fundamentally different dependent on individuals´ socioeconomic characteristics. Moreover, we also test for cut-point shifts in the data, i.e. that the five categories of self-assessed health (very good, good, medium, bad, very bad) are not constant between individuals but may also vary between the observation units.

3. Data and estimation method

For the present analysis, we use date from the German SAVE study.[1] Like in other survey studies, item non-response can lead to problems for the analysis especially for the estimation results and covariance structures [17, 49]. One possibility to deal with this problem is to delete all observations with non-responses which reduces sample size and goes along with a loss of statistical efficiency. In the SAVE data, missing values are estimated using a variant of the iterative multiple imputation procedure [18]. This is a two-step procedure where in the first step the conditional distribution of the missing variables is estimated using regression methods on a sample with complete data (see [17] for further details).[2] For the second step,

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[1] The SAVE study is conducted by the Mannheim Research Institute for the Economics of Aging (MEA) and started the in 2001. Originally, the longitudinal study on households' financial behavior focused on savings and old-age provisions but also deals with aspects of health and health behavior [17].

[2] The dataset distinguishes between core (e. g. financial data) and non-core variables (socio-demographic data and psychometric measures). The missing rates of the core variables are greater

a Markov-Chain Monte-Carlo method is used to replace the missing items in the full data set by multiple draws from the estimated conditional distribution. Hence, we can work with five complete datasets where all missings are replaced by imputed values.[3] These datasets differ slightly with respect to the imputed variables and reflect the uncertainty about the true values of the missing attributes. For all datasets, five repetitions are used to generate each imputed dataset. This procedure leads to a gain in the total observations between 10 % for males and 13 % for females.

For the analysis at hand, we use the years 2006-2008. Our dependent variable is the 5-point categorical variable self-assessed health, with 1 indicating a reported health status that is very bad and 5 a very good health status. As explanatory variables, we use socioeconomic characteristics like age, education, relative income position and labour force status. A description of the variables is presented in Table 1.[4]

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than 6 % whereas those for the non-core variables are much less than 2 % [17]. A subset of the non-core variables is used as conditioning variables or predictors for the current imputation step.

[3] Only variables on age and gender contain no missing values.

[4] Because foreigners are under-represented in the dataset, we concentrate on German citizens only.

Table 1: Variable description

variable name	label
health	self-assessed health, 1=very bad, 5=very good
d07	dummy year = 2007
d08	dummy year = 2008
partner	partner in household yes/no
children_yn	children yes/no
o_level	first public examination in secondary school yes/no
high_school	general qualification for university entrance yes/no
diploma	university degree yes/no
relat_poor	less than 50 % of the mean of equivalent household net income
prec_wealth	50-75 % of the mean of equivalent household net income
sophist_inc	125-150 % of the mean of equivalent household net income
relat_wealth	more than 150 % of the mean of equivalent household net income
full_time	full time employed (at least 35 h) yes /no
unemp	currently unemployed yes/ no
smoker	currently smoker yes/no
alcohol_freq	alcohol consumption at least 3 days a week yes/no
phys_effort	physical effort at least 1 time a week yes/no
disease_index	0 … 100; higher values indicating multimorbidity
doc1	1 to 2 doctor visits in last 12 months yes/no
doc2	3 to 6 doctor visits in last 12 months yes/no
doc3	at least 7 doctor visits in last 12 months yes/no
hospital7	at least 1 week in hospital yes/no
shorter_life	expect to live shorter than equal age group yes/no
longer_life	expect to live longer than equal age group yes/no

To cover nonlinear age effects, we group males and females into age quintiles.[5] The lowest quintile is set up by those individuals aged equal to or less than 38 years for males and 36 years for females. The highest quintile contains respondents older than 68 or 67 years, respectively. The detailed thresholds between the quintiles can be obtained from Table 2.

Table 2: Age Variables: average thresholds

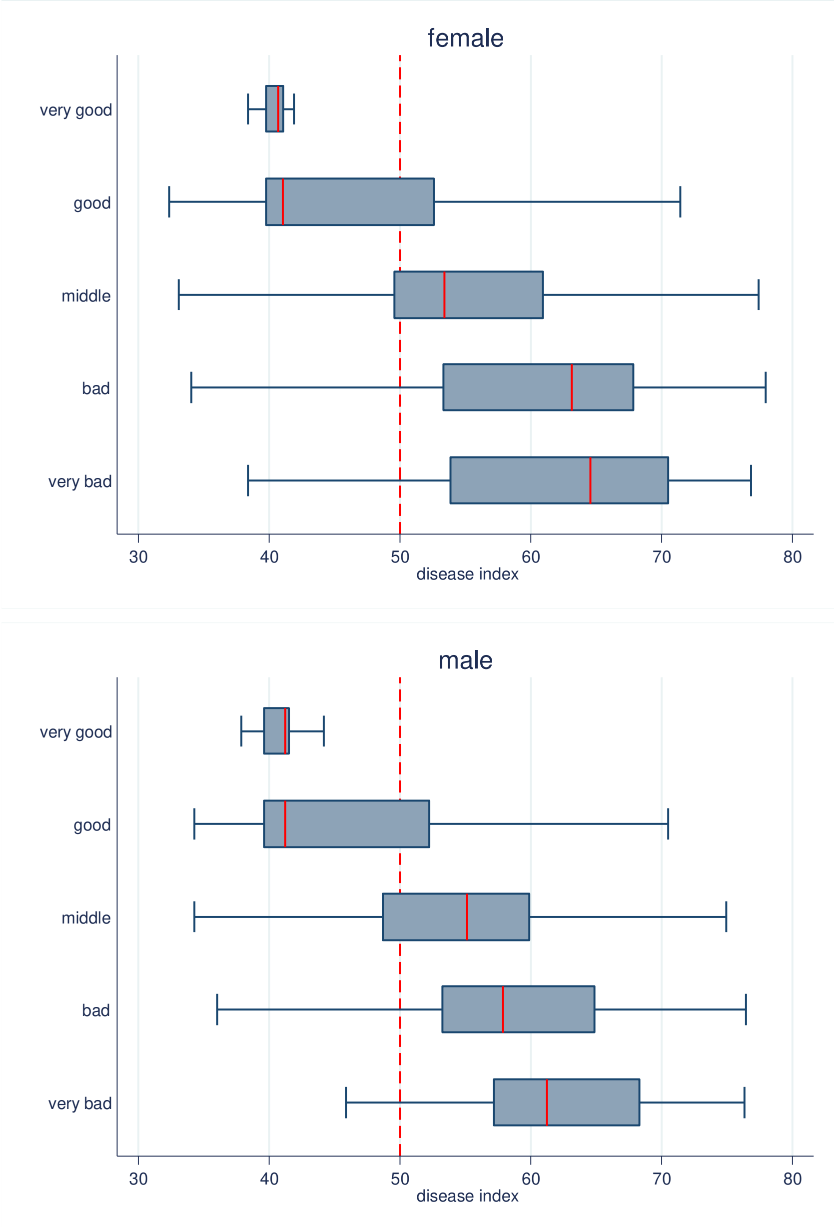
variable name	male	female
age0	<=38	<=36
age1	>38 and <=48	>36 and <=45
age2	>48 and <=58	>45 and <=55
age3	>58 and <=68	>55 and <=67
age4	>68	>67

[5] The intervals for the quintiles are averaged across years and imputations. Only small differences can be found between males and females.

Moreover, health relevant behaviour and experiences with a severe or chronic illness are included in the data set. The latter information is more related to sickness than the self-reported health but still a subjective measure. According to Kerkhofs and Lindeboom [5], we try to objectify this illness reporting. To construct our disease index, we make use of the binary variable “health problems” and regress this variable on a set of ten dummy variables indicating various forms of diseases. By doing so, we are able to weight the impact of the different illnesses on the variable “health problems”. Considering the structure of the dataset, we run this regression separately for every year and imputation and also for males and females. The prediction of the regression is then transformed to the continuous variable “disease index” ranging from 0 to 100 with mean 50 and a standard deviation of 10. Furthermore, the use of this objectified variable goes along with more variation in the explanatory variables. Therefore, a higher value of the index indicates a higher degree of multimorbidity. In comparison with the gender-specific average, an above-average index points to more illness-related problems (relatively).

The relation between our constructed index and self-assessed health can be seen from figure 1. It is obvious that a better reported health goes along with a lower value of the disease index for females as well as for males. The shadowed box resembles 50 per cent of the data in the relevant health category. One striking result is that the box for the best health status (very good) is very narrow, which means that there exists only few variation in the values of the disease index. The median is marked by the vertical line within the box. For both genders, in the category “good” the median is at the left side of the box, which means the distribution is skewed. For the two lower health categories, we observe some differences between females and males. First, the 50 % boxes are smaller for men and second, the median of females is on a larger scale. Hence, females show a larger spread of the disease index within health categories “bad” and “very bad”. With respect to the adjacent lines (whiskers), differences occur for the category “very bad”. Here the lower adjacent value is remarkably higher for males meaning that males reporting a very bad health status show a higher degree of multimorbidity.

Figure 1: Relationship between disease index and SAH by gender



In Table 3, the statistics for the first imputation are presented for males and females.[6] As can be seen for self-assessed health, no significant difference can be observed between males and females. Females tend to consume alcohol less frequently than males (13 vs. 32 per cent). For the highest education level, we find that high school and university degrees are more frequent among men. The same is true for full time working. With respect to income, we use four different dummy variables to illustrate the relative income position of a household member [19]. For age quintiles, the panel summary statistics shows a deviation from 20 %

[6] The differences between the five imputations are relatively slow.

because we use a balanced panel and average thresholds vary between the observation years.

Table 3: Summary statistics (imputation 1)

	male N=3525		**female N=3867**	
Variable	**Mean**	**SD**	**Mean**	**SD**
SAH	3.4920	0.817	3.5080	0.846
d07	0.3355	0.472	0.3366	0.473
d08	0.3296	0.470	0.3294	0.470
age1	0.2016	0.401	0.2090	0.407
age2	0.1960	0.397	0.1985	0.399
age3	0.2330	0.423	0.2356	0.424
age4	0.2104	0.408	0.1918	0.394
partner	0.7311	0.443	0.6312	0.483
children_yn	0.7616	0.426	0.8095	0.393
O_level	0.3174	0.466	0.4039	0.491
high_school	0.3222	0.467	0.2361	0.425
diploma	0.2033	0.403	0.1394	0.346
relat_poor	0.1251	0.331	0.1729	0.378
prec_wealth	0.1949	0.396	0.2474	0.432
sophist_inc	0.1149	0.319	0.0966	0.296
relat_wealth	0.1567	0.364	0.1129	0.316
full_time	0.4496	0.498	0.2067	0.405
unemp	0.0720	0.259	0.0784	0.269
smoker	0.2762	0.447	0.2552	0.436
alcohol_freq	0.3169	0.465	0.1276	0.334
phys_effort	0.6154	0.487	0.5784	0.494
disease_index	49.8966	9.946	49.8554	9.979
doc1	0.2663	0.442	0.2332	0.423
doc2	0.3426	0.475	0.3843	0.486
doc3	0.2991	0.458	0.3302	0.470
hospital7	0.1039	0.305	0.0982	0.298
shorter_life	0.1999	0.400	0.1657	0.372
longer_life	0.1624	0.369	0.1168	0.321

Index shift and cut-point shift

The effects of reporting heterogeneity can be divided into an index and a cut-point shift [13]. An index shift is present when the distribution of our variable of interest shifts completely to the right or left but the shape remains unchanged.[7] This implies a parallel shift of the associated threshold values. The relative position remains unchanged. In case of a cut-point shift, thresholds depend on the response behaviour and the relative position changes. Both shifts can be exemplified by a situation where reporting of the full population is compared to the reporting of a subgroup [14]. The differences between both forms of reporting heterogeneity can be seen from figures 2 and 3.

Figure 2: Index shift in the distribution of self-reported health

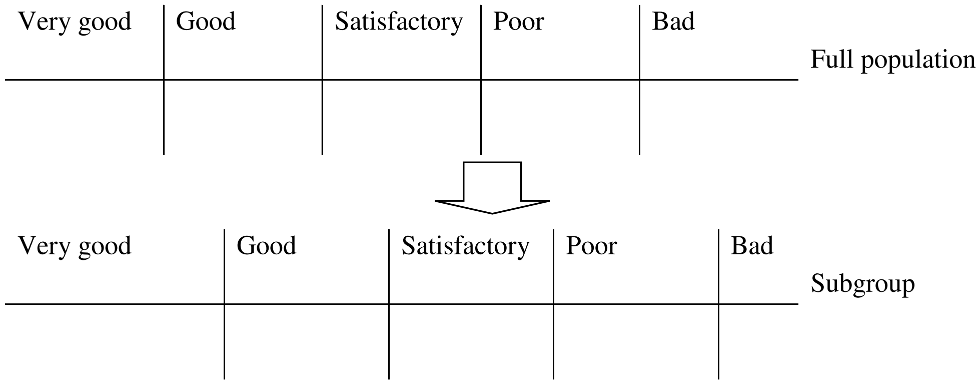
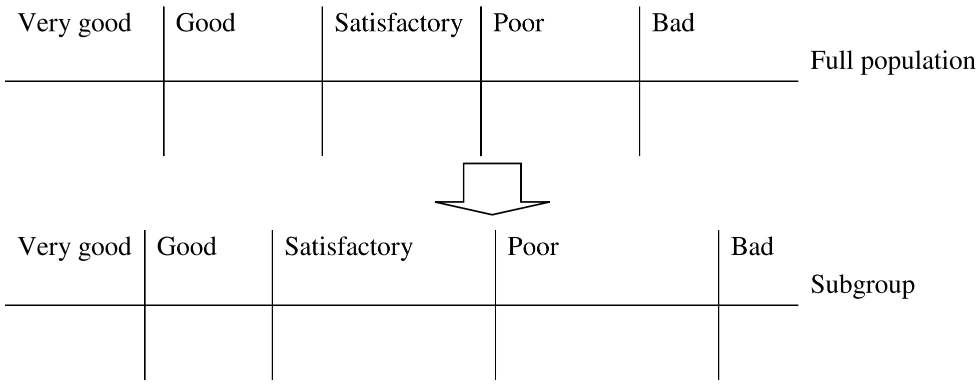


Figure 3: Cut-point shift in the distribution of self-reported health



Source: [14].

An index shift may occur when switching from the full population to a subgroup. One example is when in a specific cultural group all individuals are more reserved about their health evaluation [13]. An example for a cut-point shift is if the cultural subgroup is self-conscious about the sentence's wording in the questionnaire and if this leads to a change in the relative position of the categories e. g. in the threshold for the category 'very good'.[8]

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[7] Hernández-Quevedo et al. [14] argue that the term 'index shift' is misleading. Instead, they state that the parallel shift in the distribution may be due to a cut-point shift or due to a shift in the underlying measure of true health, i. e. the latent variable.

[8] Lindeboom and van Doorslaer [13] suggest a test procedure for both types of reporting heterogeneity. In their empirical model, they specify one equation for latent true health and one for the subjective health measure. They estimate separate ordered response models for sub-groups in their sample. The effects of the different wording are analysed by Hernández-Quevedo et al. [14]. They

Estimation approach[9]

The variable self-assessed health is a five-point categorical variable. Underlying this observed variable is the latent health status of the respondent y^*. In this case, ordered response models are the standard estimation procedure. Following the presentation in Boes and Winkelmann [21] and focusing on the cross-section case first, let y be the ordered categorical outcome, $y \in \{1, 2, \ldots, J\}$. J denotes the number of distinct categories. The cumulative probabilities of the discrete outcome are then related to a set of explanatory variables x:

$$\Pr[y \leq j \mid x] = F(\kappa_j - x'\beta) \qquad j = 1, \ldots, J \qquad (1)$$

Here, κ_j are the unknown threshold parameters and βs are the unknown coefficients.[10] The function *F* is often replaced by a standard normal or logistic distribution. In the first case, an ordered probit model results, the second case is an ordered logit model. Including the underlying latent variable one gets:

$$y = j \quad \text{if and only if} \quad \kappa_{j-1} \leq y^* = x'\beta + u < \kappa_j \qquad j = 1, \ldots, J$$

This means that the thresholds divide the real line (y^*) into *J* categories. Moreover, observable and unobservable factors influence the latent variable health. For the latter factors, a zero mean and a constant variance is assumed, e.g. $\sigma^2 = 1$ for the ordered probit model.

The probability that a respondent reports his health status to be in category j can then be written as:

$$\Pr[y = j \mid x] = F(\kappa_j - x'\beta) - F(\kappa_{j-1} - x'\beta) \qquad (2)$$

For identification purposes, it is necessary to set the constant of the regression to zero and to assume a constant variance. One obstacle to the ordered probit model is the single index or parallel regression assumption [22]. From equation (1) it follows that the coefficient vector β is the same for all categories *j*. This means that with the increase of an independent variable, the cumulated distribution shifts

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assume that a parallel shift in the thresholds that is common to all respondents can be viewed as the simplest form of an index shift. While testing for an index shift is possible in ordered response models like ordered probit, the test of a cut-point shift is implemented using a generalized ordered probit model that allows the parameter to vary between the different categories of the reported health variable.

[9] Greene and Hensher [20] discuss aspects of heterogeneity in ordered choices and present a detailed description of the generalized ordered probit model.

to the right or left but there is no shift in the slope of the distribution. Hence, one can compare an ordered response model to one in which a set of binary response models with different intercepts is estimated. Such a change in the intercept leads to a shift in the probability curve but leaves the slope unchanged. Relaxing this assumption and allowing the indices to differ across the outcomes leads to the generalized ordered probit model. Here, the threshold parameters depend on the covariates:

$$\kappa_j = \tilde{\kappa}_j + x'\gamma_j \,,$$

where γ_j are the influence parameters of the covariates on the thresholds. Entering the threshold equation above into the cumulative probability of the generalized ordered probit model leads to the following expression:

$$\Pr[y \le j \mid x] = F(\tilde{\kappa}_j + x'\gamma_j - x'\beta) = F(\tilde{\kappa}_j - x'\beta_j) \qquad j = 1, \dots, J \tag{3}$$

As one can see from equation (3), the coefficients of the covariates and the threshold coefficients cannot be identified separately when the same set of variables x is used. Hence, it follows that $\beta_j = \beta - \gamma_j$ and that the generalized ordered probit model has one index $x'\beta_j$ for each category j of the outcome variable.[11] This approach leads to the estimation of J-1 binary probit models [23]. The first model estimates category 1 versus categories 2,.., J; the second model categories 1 and 2 versus 3,.., J. Equation J-1 then compares the choice between categories 1,.., J-1 versus category J. This specification allows for individual heterogeneity in the β-parameters that leads to heterogeneity across the categories of the dependent variable.

For our panel data, we use a random effects generalized ordered probit approach [24]. More formally, let SAH be an ordinal variable which takes on the values y = 1, …, J. For the data at hand, i denotes the cross-sectional unit and t the time dimension. In contrast to the cross-section representation, the outcome probabilities are conditional on the individual effect α_i:

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[10] One assumption on the threshold parameters is that $\kappa_j > \kappa_j$-1, $\forall$j and that $\kappa_J = \infty$ and $\kappa_0 = -\infty$.

[11] The generalized ordered probit model nests the standard ordered probit model with the restriction that $\beta_1 = \dots = \beta_{J-1}$.

$$P(y_{it}=1\mid x_{it},\alpha_i)=F\left(-x_{it}^{'}\beta_1-\alpha_i\right)$$
$$P(y_{it}=y\mid x_{it},\alpha_i)=F\left(-x_{it}^{'}\beta_y-\alpha_i\right)-F\left(-x_{it}^{'}\beta_{y-1}-\alpha_i\right) \qquad y=2,\ldots,J-1$$
$$P(y_{it}=J\mid x_{it},\alpha_i)=1-F\left(-x_{it}^{'}\beta_{J-1}-\alpha_i\right) \qquad (4)$$

For the individual effects, a zero mean and a constant variance σ^2 is assumed so that $\rho=\sigma^2/(1+\sigma^2)$. As for the cross-section version of the generalized ordered probit model, the approach allows several of the β_y to vary across the categories. Therefore, using panel data allows for the inclusion of two kinds of heterogeneity. First, unobserved individual heterogeneity is captured by our random effects specification of the ordered probit model. Second, differences in the cut-points and therefore in the beta coefficients represent the observed heterogeneity in the reporting of the self-assessed health variable.

For the estimation of the random effects generalized ordered probit model, we combine an iterative procedure proposed by Williams [23] with the random effects estimation command regoprob by Boes [24].[12] First, a totally unconstraint model (all coefficients varying) is estimated. Then we apply Wald tests on each variable to prove whether the coefficients differ across equations. The least significant variable is then constraint to have equal effects, and the model is refitted with constraints and the process is repeated as long as no more insignificant variables result. Moreover, a global Wald test on the full model with constraints is applied that confirms the null hypothesis that the parallel regression assumption is not violated.[13]

4. Results

Tables 4 and 5 present selected results from our estimation for males and females. The full estimation results containing constraint and unconstraint coefficients are shown in the appendix. We outline key results for those variables for which the parallel regression assumption is rejected. For these variables, we can conclude

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[12] A complete description of the procedure can be found in Pfarr et al. [25]. The related user-written Stata program regoprob2 is available at the SSC archive.

[13] The estimation with different imputations requires some caution with respect to the 'averaging' of the results [26]. For the total results, it follows that the coefficient vector of the multiple imputation analysis is given by the mean of the single estimations while for the variance-covariance esti-

the presence of a cut-point shift leading to the observed heterogeneity of SAH. In the tables, we display the results of two types of estimations. The last column contains the ordered probit estimation and the other four columns show the results for the generalized ordered probit model. The latter consists of four binary models. As stated above, the first model estimates category 1 versus categories 2,.., 5 the second model categories 1 and 2 versus 3,.., 5 and so on. If an explanatory factor is included in tables 4 and 5 the coefficients are varying between the categories. This means that these variables are then responsible for a cut-point shift in the distribution of SAH and therefore cause the observed heterogeneity.

One main finding from the generalized ordered probit is that observed heterogeneity of SAH is caused by different variables for males and females. Explanatory variables are classified in income-related, socio-economic, and health-related factors. Health-related variables (smoking, alcohol consumption, disease index, doctor visits) vary between categories for males and females whereas income variation is only found for males and the socio-economic factors (age, education) drive the observed heterogeneity in health reporting for females. One has to emphasise that all explanatory variables enter the estimation but the variables given in tables 4 and 5 drive the observed heterogeneity.

Table 4: Combined selected results generalized ordered probit and ordered probit; males

	1 vs. 2-5	**1-2 vs. 3-5**	**1-3 vs. 4-5**	**1-4 vs. 5**	**Ordered probit**
relat_poor	-0.9415***	-0.5349***	0.0448	0.5623***	-0.0067
prec_wealth	-0.2517	-0.4607***	-0.0595	0.0018	-0.1439*
relat_wealth	0.7101	-0.2022	0.1426	0.0510	0.0660
unemp	1.0729**	-0.2617	0.2106	0.2851	0.1164
phys_effort	0.9361***	0.2605**	0.3387***	0.0949	0.2977***
disease_index	-0.0428***	-0.0400***	-0.0602***	-0.0398***	-0.0525***
doc1	0.2525	0.0548	0.0292	-0.5457***	-0.2389**
doc2	-0.2568	-0.1312	-0.4654***	-0.6644***	-0.5619***
hospital7	-1.0575***	-0.6520***	-0.4252***	-0.6671	-0.5802***
N	3525				

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

mate one has to distinguish between the within- and the between-imputation variance-covariance matrix.

Table 5: Combined selected results generalized ordered probit and ordered probit; females

	1 vs. 2-5	**1-2 vs. 3-5**	**1-3 vs. 4-5**	**1-4 vs. 5**	**Ordered probit**
age4	-0.2616	-0.7781***	-1.4515***	-1.5447***	-1.2503***
partner	0.3274*	0.0704	0.0637	-0.2999**	-0.0220
O_level	0.3179	-0.1326	0.2341**	-0.0372	0.1004
high_school	0.4137	0.0485	0.4295***	0.1021	0.2781**
alcohol_freq	0.1242	0.0012	0.2628**	-0.2167	0.0848
disease_index	-0.0424***	-0.0625***	-0.0739***	-0.0474***	-0.0649***
doc3	-0.9857***	-1.1806***	-1.0813***	-0.7009***	-1.0324***
hospital7	-0.7642***	-0.5168***	-0.2142*	-0.0629	-0.3768***
shorter_life	-0.4911***	-0.6162***	-0.8122***	-0.2980	-0.6487***
longer_life	-0.3322	0.2768	0.5580***	0.8649***	0.6362***
N	3867				

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In a simple ordered probit estimation, the impact of income on SAH is weak or not significant for males. In contrast, generalized ordered probit estimates show that individual health varies with income. In more detail, relative poor individuals tend to report a very bad or bad health status more often. Surprisingly, for the highest health status (1-4 vs. 5) we derive a positive effect of relative poverty on SAH, e.g. fighting poverty is important for but not identical to improving health. Moreover, the constraint variable precarious wealth goes along with a significantly negative effect on the reported health level. In addition, the impact of relative wealth is significantly positive. In the female estimation, all the income variables are constraint.

Within the group of variables causing heterogeneity for females, education (O-level and high school) is only significantly positive for those in satisfactory health conditions (categories 1-3 vs. 4-5). Standard ordered probit estimation shows no significant impact for O-level. Compared to women with a rather low knowledge stock, the positive influence of education on SAH implies that the probability of being in a good health status increases with better education. The ordered probit model for women shows no significance for a university degree; this is the only training variable with significance in the male sample.

Doing sport (phys-effort) at least 1 time a week has a different impact for males and females. In the female group, the effect is constant and significantly positive, in the males group the effect varies between the categories of SAH. Practicing sport lowers the probability for reporting a bad health status significantly while the effect on the highest health category is insignificant. Sport may generate health benefits: through direct participation as well as communication, educational benefits and social mobilization. Because physical inactivity is a primary risk for chronic diseases, sports can play a critical role in slowing the spread of chronic diseases, reducing their social and economic burden, and saving lives. But not to be forgotten sports has also the potential for damaging health. Athletic injuries or other health problems relate directly to physical activity. All in all the impact of sports on health remains indefinite.

As regards health care utilisation (doctor visits), one would expect that 1 or 2 doctor visits in the last year have little impact on individual health status because these few visits have more or less preventive character. This view of health care demand is rejected for males. While the ordered probit model suggests a significant negative impact, the generalized model shows a negative effect only for the best health status (1-4 vs. 5). For the health effect of just a few doctor visits, one cannot give a clear-cut answer. Regarding 3-6 visits (doc2), we find a significantly negative influence for the two upper categories of SAH. Having more than 6 doctor visits in the last twelve months (doc3) has the expected negative sign for all categories but is only varying throughout the categories for females. Another key result is that reporting heterogeneity is found for doctor visits but with gender-specific characteristics.

Our disease index is varying for both males and females. All effects are highly significant and negative. They are strongest when comparing categories 1-3 with 4-5 resulting in a tendency to report a health status satisfactory or lower. This results in a grouping of categories 1-3 and 4-5. This means that health problems caused by different forms of illnesses and consequently multimorbidity leads to reporting heterogeneity. Subsequently, comparing illness-related questions and questions on self-assessed health leads to the conclusion that heterogeneity is driven by disease experiences.

To sum up, the estimation of a generalized ordered probit strongly suggest that there is a cut-point shift in the distribution of self-assessed health.[14] Moreover, our

[14] While our analysis helps to identify possible cut-point shift it remains unclear whether there is also an index shift. Following the approach in Hernández-Quevedo et al. [14], we introduced time dummies for the observation years. Only for males, the year 2008 has a strong significant negative effect.

estimations provide evidence that the variables causing observed heterogeneity in health status differ notably between males and females. As the generalized ordered probit estimation points out, income-related, socio-economic, and health-related factors suggest that reporting heterogeneity should be taken into account. As a consequence, caution is necessary when using self-reported measures of health in empirical studies. Moreover, the results also suggest that the influence of the factors above should be considered when designing questionnaires.

5. Conclusion

How reliable are individual answers about self-assessed health? A lot of empirical studies use self-assessed health as qualitative five-point categorical variable on the left hand side of ordered probit models. In the paper, we express doubts that a random effects ordered probit model is a suitable approach for analysing determinants of self-assessed health. This model neglects the fact that the classification into the five subscales depends on socioeconomic as well as health related variables. Moreover, the answering behaviour differs between female and male respondents. The results of a random effects generalized ordered probit estimation help on the one hand to detect a possible heterogeneity in reporting behaviour and on the other hand to identify possible sources of heterogeneity. In contrast to a random effects ordered probit estimation, our approach combines the detection of observed heterogeneity in categorical variables with the inclusion of unobserved individual heterogeneity using panel data.

Our research contributes to the diversified literature on a possible reporting bias in self-assessed health. Unlike studies on labour force participation or income inequality, we do not focus on reporting behaviour in a special case. Instead, we try to show that heterogeneity may depend on gender-specific variables. Among others, experience with different kinds of illnesses may be one source of different reporting behaviour. Income as a possible source of heterogeneity is more important for men than for women. Other gender differences exist with respect to the influence of education on the reporting behaviour of health. Our estimation approach helps to detect how socioeconomic determinants and health experiences differently influence the individual reporting behaviour.

Hence, our evidence relates to the question how reliably a person completes health related items in a questionnaire. Generally spoken, evaluating questionnaires from panel data based on population subgroups such as migrants, children, older people or questionnaires from different countries run the risk to compare apples and oranges if the problem of reporting heterogeneity is not adequately taken into account. Especially the results of the disease index indicate that individual experiences in the past drive the answering behaviour. Thus, to control for heterogeneous responses to the SAH question it is required to include individual illness episodes in the questionnaire. Using such information is important to assess the correct health status but this information has to be weighted in order to retrieve an objectified measure of health. Otherwise, one would explain the heterogeneity of self-assessed health with the subjective illness perception.

Our findings show that a widespread and common measure of health like SAH is prone to heterogeneity and that objectified health indicators can be used to detect this bias.

For further research, it would be interesting to evaluate different approaches to objectify additional health indicators. One way may be to capture the effects of partner's health status and disease experience on the reporting of health. With such an approach it would be possible to include possible psychological externalities in an empirical investigation. Moreover, as our results only represent German individuals, one has to ask whether the sources of observed heterogeneity differ across countries.

6. Appendix

Table 1: Random effects ordered probit estimates

	male N=3525		female N=3867	
	coefficient	**p-value**	**coefficient**	**p-value**
d07	-0.0629***	(0.240)	-0.0806***	(0.117)
d08	-0.2348***	(0.000)	-0.0866***	(0.095)
age1	-0.2983***	(0.013)	-0.4130***	(0.000)
age2	-0.7061***	(0.000)	-0.9905***	(0.000)
age3	-0.6024***	(0.000)	-0.9202***	(0.000)
age4	-0.5419***	(0.001)	-1.2503***	(0.000)
partner	0.0851***	(0.336)	-0.0220***	(0.781)
children_yn	-0.0835***	(0.395)	0.1623***	(0.083)
O_level	0.0166***	(0.849)	0.1004***	(0.228)
high_school	0.1336***	(0.214)	0.2781***	(0.015)
diploma	0.2090***	(0.059)	-0.0281***	(0.808)
relat_poor	-0.0067***	(0.952)	-0.2807***	(0.003)
prec_wealth	-0.1439***	(0.075)	-0.2687***	(0.000)
sophist_inc	-0.0127***	(0.894)	0.1525***	(0.123)
relat_wealth	0.0660***	(0.490)	0.2064***	(0.045)
full_time	0.2544***	(0.015)	0.1453***	(0.108)
unemp	0.1164***	(0.404)	-0.5249***	(0.000)
smoker	-0.2434***	(0.004)	-0.1000***	(0.224)
alcohol_freq	0.0963***	(0.165)	0.0848***	(0.374)
phys_effort	0.2977***	(0.000)	0.2907***	(0.000)
disease_index	-0.0525***	(0.000)	-0.0649***	(0.000)
doc1	-0.2389***	(0.027)	-0.1427***	(0.253)
doc2	-0.5619***	(0.000)	-0.4931***	(0.000)
doc3	-1.1394***	(0.000)	-1.0324***	(0.000)
hospital7	-0.5802***	(0.000)	-0.3768***	(0.000)
shorter_life	-0.6534***	(0.000)	-0.6487***	(0.000)
longer_life	0.5095***	(0.000)	0.6362***	(0.000)
ρ	0.5405***	(0.000)	0.5695***	(0.000)

p-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Random effects generalized ordered probit males

	1 vs. 2-5		1-2 vs. 3-5		1-3 vs. 4-5		1-4 vs. 5	
	coeff.		**coeff.**		**coeff.**		**coeff.**	
d07	-0.0641	(0.240)	-0.0641	(0.240)	-0.0641	(0.240)	-0.0641	(0.240)
d08	-0.2361	(0.000)	-0.2361	(0.000)	-0.2361	(0.000)	-0.2361	(0.000)
age1	-0.2699	(0.026)	-0.2699	(0.026)	-0.2699	(0.026)	-0.2699	(0.026)
age2	-0.6643	(0.000)	-0.6643	(0.000)	-0.6643	(0.000)	-0.6643	(0.000)
age3	-0.6114	(0.000)	-0.6114	(0.000)	-0.6114	(0.000)	-0.6114	(0.000)
age4	-0.5300	(0.002)	-0.5300	(0.002)	-0.5300	(0.002)	-0.5300	(0.002)
partner	0.0958	(0.288)	0.0958	(0.288)	0.0958	(0.288)	0.0958	(0.288)
children_yn	-0.0928	(0.352)	-0.0928	(0.352)	-0.0928	(0.352)	-0.0928	(0.352)
O_level	0.0272	(0.758)	0.0272	(0.758)	0.0272	(0.758)	0.0272	(0.758)
high_school	0.1267	(0.246)	0.1267	(0.246)	0.1267	(0.246)	0.1267	(0.246)
diploma	0.2444	(0.030)	0.2444	(0.030)	0.2444	(0.030)	0.2444	(0.030)
relat_poor	-0.9415	(0.001)	-0.5349	(0.003)	0.0448	(0.745)	0.5623	(0.001)
prec_wealth	-0.2517	(0.299)	-0.4607	(0.001)	-0.0595	(0.561)	0.0018	(0.990)
sophist_inc	-0.0050	(0.959)	-0.0050	(0.959)	-0.0050	(0.959)	-0.0050	(0.959)
relat_wealth	0.7101	(0.103)	-0.2022	(0.234)	0.1426	(0.220)	0.0510	(0.752)
full_time	0.2707	(0.011)	0.2707	(0.011)	0.2707	(0.011)	0.2707	(0.011)
unemp	1.0729	(0.021)	-0.2617	(0.207)	0.2106	(0.211)	0.2851	(0.209)
smoker	-0.2331	(0.007)	-0.2331	(0.007)	-0.2331	(0.007)	-0.2331	(0.007)
alcohol_freq	0.0992	(0.159)	0.0992	(0.159)	0.0992	(0.159)	0.0992	(0.159)
phys_effort	0.9361	(0.000)	0.2605	(0.015)	0.3387	(0.000)	0.0949	(0.415)
disease_index	-0.0428	(0.001)	-0.0400	(0.000)	-0.0602	(0.000)	-0.0398	(0.000)
doc1	0.2525	(0.672)	0.0548	(0.795)	0.0292	(0.821)	-0.5457	(0.000)
doc2	-0.2568	(0.395)	-0.1312	(0.428)	-0.4654	(0.000)	-0.6644	(0.000)
doc3	-0.9776	(0.000)	-0.9776	(0.000)	-0.9776	(0.000)	-0.9776	(0.000)
hospital7	-1.0575	(0.000)	-0.6520	(0.000)	-0.4252	(0.001)	-0.6671	(0.100)
shorter_life	-0.6532	(0.000)	-0.6532	(0.000)	-0.6532	(0.000)	-0.6532	(0.000)
longer_life	0.5204	(0.000)	0.5204	(0.000)	0.5204	(0.000)	0.5204	(0.000)
_cons	7.2280	(0.000)	5.4942	(0.000)	3.7745	(0.000)	0.2394	(0.553)
ρ	0.5480	(0.000)						
N	3525							

p-values in parentheses

Table 3: Random effects generalized ordered probit females

	1 vs. 2-5		1-2 vs. 3-5		1-3 vs. 4-5		1-4 vs. 5	
	coeff.		**coeff.**		**coeff.**		**coeff.**	
d07	-0.0770	(0.140)	-0.0770	(0.140)	-0.0770	(0.140)	-0.0770	(0.140)
d08	-0.0875	(0.097)	-0.0875	(0.097)	-0.0875	(0.097)	-0.0875	(0.097)
age1	-0.3778	(0.001)	-0.3778	(0.001)	-0.3778	(0.001)	-0.3778	(0.001)
age2	-0.9465	(0.000)	-0.9465	(0.000)	-0.9465	(0.000)	-0.9465	(0.000)
age3	-0.8838	(0.000)	-0.8838	(0.000)	-0.8838	(0.000)	-0.8838	(0.000)
age4	-0.2616	(0.333)	-0.7781	(0.000)	-1.4515	(0.000)	-1.5447	(0.000)
partner	0.3274	(0.089)	0.0704	(0.567)	0.0637	(0.500)	-0.2999	(0.014)
children_yn	0.1694	(0.073)	0.1694	(0.073)	0.1694	(0.073)	0.1694	(0.073)
O_level	0.3179	(0.125)	-0.1326	(0.311)	0.2341	(0.021)	-0.0372	(0.792)
high_school	0.4137	(0.173)	0.0485	(0.788)	0.4295	(0.001)	0.1021	(0.529)
diploma	-0.0085	(0.942)	-0.0085	(0.942)	-0.0085	(0.942)	-0.0085	(0.942)
relat_poor	-0.2855	(0.003)	-0.2855	(0.003)	-0.2855	(0.003)	-0.2855	(0.003)
prec_wealth	-0.2727	(0.000)	-0.2727	(0.000)	-0.2727	(0.000)	-0.2727	(0.000)
sophist_inc	0.1595	(0.112)	0.1595	(0.112)	0.1595	(0.112)	0.1595	(0.112)
relat_wealth	0.2068	(0.047)	0.2068	(0.047)	0.2068	(0.047)	0.2068	(0.047)
full_time	0.1251	(0.170)	0.1251	(0.170)	0.1251	(0.170)	0.1251	(0.170)
unemp	-0.4859	(0.000)	-0.4859	(0.000)	-0.4859	(0.000)	-0.4859	(0.000)
smoker	-0.0987	(0.233)	-0.0987	(0.233)	-0.0987	(0.233)	-0.0987	(0.233)
alcohol_freq	0.1242	(0.683)	0.0012	(0.995)	0.2628	(0.031)	-0.2167	(0.176)
phys_effort	0.2972	(0.000)	0.2972	(0.000)	0.2972	(0.000)	0.2972	(0.000)
disease_index	-0.0424	(0.000)	-0.0625	(0.000)	-0.0739	(0.000)	-0.0474	(0.000)
doc1	-0.1408	(0.270)	-0.1408	(0.270)	-0.1408	(0.270)	-0.1408	(0.270)
doc2	-0.5137	(0.000)	-0.5137	(0.000)	-0.5137	(0.000)	-0.5137	(0.000)
doc3	-0.9857	(0.000)	-1.1806	(0.000)	-1.0813	(0.000)	-0.7009	(0.000)
hospital7	-0.7642	(0.000)	-0.5168	(0.000)	-0.2142	(0.095)	-0.0629	(0.806)
shorter_life	-0.4911	(0.006)	-0.6162	(0.000)	-0.8122	(0.000)	-0.2980	(0.114)
longer_life	-0.3322	(0.329)	0.2768	(0.214)	0.5580	(0.000)	0.8649	(0.000)
_cons	6.9393	(0.000)	7.1164	(0.000)	4.8306	(0.000)	1.0404	(0.014)
ρ	0.5715	(0.000)						
N	3867							

p-values in parentheses

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