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Item Nonresponse in Wages: Testing for Biased Estimates in Wage Equations

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Michael Fertig and Katja Görlitz[1]

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Abstract

This paper investigates how to test and correct for nonresponse selection bias induced by missing income information when estimating wage functions. The novelty is to use the variation in interviewer-specific response rates as exclusion restriction within the framework of a sample selection model.

JEL Classification: J30

Keywords: Item nonresponse; wages

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1. Introduction

It is a well-known fact that item nonresponse is particularly high when income and wage information are conducted in surveys. If the response inclination is systematically related to wages, the estimates of wage equations could suffer from serious biases (Zweimüller 1992). Missing wage information is still a rather neglected problem in empirical studies estimating wage functions. A common way to account for nonresponse is to eliminate missing cases. Such a procedure assumes implicitly that wages are missing at random. The finding that item nonresponse on wage questions is more common in the tails of the income distribution (Riphahn and Serfling 2005) seems to be at odds with such an assumption.

In this study, we introduce an approach to test for nonresponse bias within the Heckman selection framework by using interviewer quality as exclusion restriction. The quality of an interviewer is approximated by the share of conducted interviews with non-missing wage information. We find that interviewer quality is a strong predictor of individuals' response behavior and works well to test for nonresponse bias. One recommendation to survey administrators is, therefore, to provide at least information on interviewer-IDs in telephone and oral interviews. No detailed interviewer characteristics are needed any further.

2. Data and empirical strategy

The empirical investigation is conducted using data from the German linked employer-employee data set "WeLL" that was designed to analyze continuous training activities of individuals. The first wave of the WeLL data covers 6,404 employees who were employed in December 31, 2006 in one of 149 establishments that were selected for the survey.[1] Employee interviews were carried out between October 2007 and January 2008 using computer assisted telephone interviews (CATI). Besides information on further training activities, there is additional information on socio-demographics, educational attainment as well as job characteristics. For the analyses, some data restrictions were made. Specifically, we exclude individuals with no job during the time of the interview and with no information on core variables. These restrictions reduced the sample size by 3% and by 2%, respectively. Furthermore, few observations with implausible information and outliers are deleted as well. The final data set contains 6,054 observations from previously 6,404.

A unique feature of the utilized data is that additional information can be merged from administrative sources of the social security system (which covers approximately 80% of the German workforce). In addition to information on employees' labor market history, the administrative data contains exact information on wages since 1975 for West and 1992 for East Germany. However, German data protection regulations do not allow merging data from different sources without respondents' permission. Therefore, the questionnaire of the WeLL data contained the opportunity for respondents to declare their agreement to link administrative information to their WeLL survey data. In our sample, the average rate was 91%. Hence, for the vast majority of respondents we are able to use wage information from administrative sources which has the advantage that they are unaffected by measurement error or recall bias.

[1] The firms were chosen according to pre-defined criteria (e.g. firm size between 100 and 2000 employees, manufacturing and service sector firms). For further information, see Bender et al. (2009).

To investigate whether respondent's approval to merge data from administrative sources is systematically related to wages and thereby inducing biases in wage functions, a sample selection model is estimated (Heckman 1979) that can be described as follows:

$$y_{1i}^{*} = x_{1i}'\beta_1 + \varepsilon_{1i} \quad (1)$$

$$y_{2i}^{*} = x_{2i}'\beta_2 + \varepsilon_{2i} \quad (2)$$

$$y_{2i} = \begin{cases} 1 \ if \ y_{2i}^{*} > 0 \\ 0 \ if \ y_{2i}^{*} \le 0 \end{cases}$$

$$y_{1i} = \begin{cases} y_{1i}^{*} & if \ y_{2i}^{*} > 0 \\ unobserved & if \ y_{2i}^{*} \le 0 \end{cases}.$$

The outcome equation (1) is derived from a Mincer earnings function (Mincer 1974). The selection equation (2) indicates whether individuals approved on merging their survey data with administrative sources. y_1^{*} and y_2^{*} are latent variables. The log gross monthly wage y_1 of individual i is only observed for individuals when the income information is observed (i.e. $y_2 = 1$). It is unobserved when individuals denied merging (i.e. $y_2 = 0$). The vector x_1 contains individual characteristics (including socio-demographics, education and experience) as well as job characteristics. Additionally, x_2 includes the quality of the interviewer as exclusion restriction.[2] In particular, interviewer quality is approximated by a binary variable that is one, if the interview was conducted by an interviewer who has an above-average approval rate of more than 95% while conducting at least five interviews.[3]

This variable could represent e.g. unobservable interviewer characteristics such as experience as interviewer or having a sympathetic and trustworthy voice or interviewers' experience with the survey. These characteristics are assumed to be correlated with individuals' response inclination but unrelated to wages. The error terms ε_1 and ε_2 are assumed to follow a bivariate normal distribution. If they are correlated with each other (indicated by ρ), missing wage information cannot be ignored in the regressions and a sample selection correction needs to be applied. Estimation is carried out by the efficient Maximum likelihood (ML) approach as well as by Heckmans' two step procedure.[4] Variable names and sample means are presented in Table 1.

[2] Our approach follows the literature on interviewer effects as determinants of individuals' response decision (see e.g. Sousa-Poza and Henneberger 2000). One difference is that it can be applied in the absence of detailed interviewer characteristics which are sometimes not available in data sets e.g. because of data protection reasons.

[3] 97% of all interviews were conducted by interviewers with at least five interviews. Sensitivity checks show that using alternatively six, seven or eight interviews as threshold does not change the results.

[4] In the estimation, we ignore right-censoring of the log monthly wage (which occurs because of top-coding at the upper contribution limit to the social security system) since it is out of the scope of this paper to present unbiased results of the wage equation.

Table 1: Variable description and summary statistics

Variable	Description	Mean
ln(wage)	Logarithm of gross monthly wages	7.91
		(0.53)
Male	Dummy variable: 1 for males, 0 otherwise	0.63
German	Dummy variable: 1 for born in Germany, 0 otherwise	0.94
Married	Dummy variable: 1 for married employees, 0 otherwise	0.73
Children (y/n)	Dummy variable: 1 for employees with underaged children, 0 otherwise	0.38
Male*Children	Interaction term between male and child	0.25
Years of schooling	Years of schooling	12.98
Potential experience	Potential experience (Age-years of schooling-6)	26.17
Training incidence	Dummy variable: 1 for training participation in last 2 years, 0 otherwise	0.65
Tenure	Tenure in current job (in months)	207.48
White collar employee	Dummy variable: 1 for white collar workers, 0 otherwise	0.65
Full time job	Dummy variable: 1 for employees working full-time, 0 otherwise	0.84
Temporary contract	Dummy variable: 1 for employees with temporary contract, 0 otherwise	0.06
Approval to merge wages	Dummy variable: 1 for approval, 0 otherwise	0.91
Interviewer quality	Dummy variable: 1 for interviewer with approval rate of >95% and who conducted at least five interviews, 0 otherwise	0.23

Notes: 6,054 observations. Standard deviation in parantheses.

3. Results

In Table 2, the results of the Probit selection equation are summarized separately for a specification excluding and including interviewer quality (column 1 and column 2, respectively). Among respondents' characteristics, there are only few statistically significant results. Having children and having participated in training are positively correlated with approving to merge wage information.[5] The most important predictor, however, is interviewer quality that increases the likelihood to give one's approval by 8 percentage points. Furthermore, we also observe a remarkable increase in the pseudo R^2 by a factor of more than three after introducing interviewers' quality in the regression.[6]

Table 3 presents the sample selection model results. Regardless of using the ML approach or the two-step procedure, a similar conclusion can be drawn. When using interviewer quality as exclusion restriction, there is no evidence that deleting observations with missing wage information from the regression would lead to biased results. This result contrasts to the findings of Zweimüller (1992) who identifies a large bias from ignoring missing cases. It is, however, similar to the conclusion drawn by Sousa-Poza and Henneberger (2000) who do not find evidence of a selection bias. One reason could be differences in the refusal rate. While Zweimüller (1992) is confronted with a unit nonresponse rate of 40%, Sousa-Poza and Henneberger (2000) is concerned with a rate of 14% and in our data set we face an approval rate of 9%.

[5] Since we look at the approval rate to merge further data instead of looking at a direct measure of refusing to provide wage information, it is difficult to compare these results with other studies.
[6] These results remain unchanged when clustering the results at the interviewer level (287 clusters).

Table 2: Determinants of the response decision

	Without interviewer quality		Including interviewer quality	
	Marg. Eff.	Std. Err.	Marg. Eff.	Std. Err.
Male	0.007	0.010	0.005	0.009
German	0.027	0.017	0.031	0.017
Married	0.006	0.010	0.006	0.009
Children (y/n)	0.027 **	0.019	0.023 **	0.012
Male*children	-0.042 **	0.019	-0.038 **	0.017
Years of schooling	0.002	0.002	0.002	0.002
Potential experience	0.001	0.002	0.001	0.002
Potential experience squared	0.000	0.000	0.000	0.000
Training incidence	0.033 ***	0.008	0.029 ***	0.008
Tenure	0.000	0.000	0.000	0.000
Skilled white collar worker	-0.016	0.009	-0.014	0.008
Full time contract	0.023	0.013	0.021	0.012
Temporary contract	-0.001	0.015	-0.005	0.015
Interviewer quality	No		0.084 ***	0.006
Observations	6,054		6,054	
Pseudo R^2	0.0143		0.0524	

Notes: Probit model. Dependent variable: Approval to merge wage information (y/n). Marginal effects are shown. Significance level: *** 1%, ** 5%.

Table 3: Estimation results of sample selection correction model

	Maximum Likelihood		Two-step model	
	Coeff.	Std. Err.	Coeff.	Std. Err.
Wage equation				
Male	0.206 ***	0.014	0.206 ***	0.014
German	-0.002	0.021	0.000	0.021
Married	-0.008	0.013	-0.008	0.013
Children (y/n)	-0.081 ***	0.019	-0.079 ***	0.019
Male*children	0.148 ***	0.022	0.145 ***	0.022
Years of schooling	0.046 ***	0.002	0.046 ***	0.002
Potential experience	0.014 ***	0.002	0.014 ***	0.002
Potential experience squared	-0.0003 ***	0.000	-0.0003 ***	0.000
Training incidence	0.121 ***	0.011	0.123 ***	0.011
Tenure	0.001 ***	0.000	0.001 ***	0.000
Skilled white collar worker	0.181 ***	0.013	0.180 ***	0.013
Full time contract	0.642 ***	0.016	0.644 ***	0.016
Temporary contract	-0.124 ***	0.022	-0.124 ***	0.022
Selection equation				
Exclusion restriction: Interviewer quality	0.829 ***	0.083	0.828 ***	0.083
ρ	0.02		0.13	
LR test, (p-value)	0.07, (0.79)			
Bootstrapped std. errors, (p-value)			0.22, (0.54)	
Observations	6,054		6,054	
Censored Observations	516		516	
Uncensored Observations	5,538		5,538	

Notes: Heckman selection model. Significance level: *** 1%, ** 5%.

4. Conclusion

The main results of this study can be summarized as follows: (i) The willingness to reveal sensitive information varies by interviewer. This variation can be used to test for biases induced by missing wage information. To apply this approach it is only necessary to have an interviewer-ID. (ii) In the WeLL data, there is no evidence of a nonresponse selection bias. Deleting observations with missing information is, thus, an appropriate way to deal with missing cases when estimating wage equations with this data. However, this result is not transferrable to other data sets. Especially when analyzing data where missing cases are more frequent, selection issues are more likely to arise and should, therefore, not be ignored.

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