Nonparametric modeling of the anchoring effect in an unfolding bracket design[1]

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Abstract

Household surveys are often plagued by item non-response on economic variables of interest like income, savings or the amount of wealth. Manski (1989,1994, 1995) shows how, in the presence of such non-response, bounds on conditional quantiles of the variable of interest can be derived, allowing for any type of non-random response behavior. Including follow up categorical questions in the form of unfolding brackets for initial item non-respondents, is an effective way to reduce complete item non-response. Recent evidence, however, suggests that such design is vulnerable to a psychometric bias known as the anchoring effect. In this paper, we extend the approach by Manski to take account of the information provided by the bracket respondents. We derive bounds which do and do not allow for the anchoring effect. These bounds are applied to earnings in the 1996 wave of the Health and Retirement Survey (HRS). The results show that the categorical questions can be useful to increase precision of the bounds, even if anchoring is allowed for.

Key words: unfolding bracket design, anchoring effect, item nonresponse, bounding intervals, nonparametrics.
JEL Classification: C14, C42, C81, D31

[1]Gauss programs used in this paper are available from the corresponding author.

1 Introduction

Household surveys are often plagued by item non-response on economic variables of interest like income, savings or the amount of wealth. For example, in the Health and Retirement Survey (HRS), a US panel often used to study socio-economic behaviour of the elderly, 12.4% of those who say they have some earnings refuse or claim they do not know their amount of these earnings. Questions on amounts of certain types of wealth often even lead to much larger non-response rates. A number of papers show how, in the presence of such non-response, bounds on conditional quantiles of the variable of interest can be derived, allowing for any type of non-random response behaviour. See, for example, Manski (1989, 1994, 1995) and Heckman (1990). In this framework, the precision with which features of the distribution of the variable of interest (such as quantiles of the income distribution) can be determined, i.e., the width between the bounds, depends on the probability of non-response. In case of substantial non-response probabilities, the approach cannot lead to reasonably precise estimates of the parameters of interest.

Including follow-up questions in the form of unfolding brackets for initial item non-respondents is an effective way to reduce complete item non-response. In the HRS example given above, 73% of the initial non-respondents do answer the question whether or not their earnings exceed $25,000, and most of these also answer a second question on either $50,000 (if the first answer was 'yes') or $5,000 (if the first answer was 'no'). Recent evidence given by Hurd et al. (1997), however, suggests that such a design leads to an "anchoring effect," a phenomenon well documented in the psychological literature: the distribution of the categorical answers is affected by the amounts in the questions (the "bids" which become "anchors"). Experimental studies have shown that even if the anchor is arbitrary and uninformative with respect to the variable of interest, it still produces large effects on the overall responses of the population (see, for example, Jacowitz et al., 1995). Using a special survey with randomized initial bids (instead of $25,000 for everybody), Hurd et al. (1997) show that the distribution is biased towards the categories close to the initial bid. They develop a parametric model to capture this anchoring phenomenon, and estimate it. Their results confirm that the anchoring effect can lead to biased conclusions on the parameters of interest if not properly accounted for.

In this paper, we extend the approach by Manski to take account of the information provided by the bracket respondents. We derive two sets of bounds, which do and do not allow for anchoring effects. The bounds which do not allow for anchoring effects are based on the assumption that the bracket information is always correct. The bounds allowing for anchoring effects relax this assumption, and replace it by the non-parametric assumption that the probability of answering a bracket question correctly is at least 0.5. This assumption is substantially weaker than the assumptions in the Hurd et al. (1997) framework.

These bounds are applied to earnings in the 1996 wave of the Health and Retirement Survey. The results show that the categorical questions can be useful to increase precision of the bounds, even if anchoring is allowed for. This also helps, for example, to improve the power of statistical tests. To illustrate this, we compare bounds for the populations of men and women, and show how the bounds which take account of bracket information can detect differences which cannot be identified by bounds based upon complete respondents' information.

The remainder of this paper is organized as follows. Section 2 elaborates on the problems associated with item nonresponse in economic surveys, and compares different ways to deal with such problems. Building up on Manski's approach, Section 3 derives bounding intervals using the unfolding bracket questions information, accounting and not accounting for anchoring effects. Section 4 describes the HRS data used in the empirical illustration. Section 5 explains the estimation technique and discusses the empirical results. Section 6 concludes.

2 Item Non-response in Household Surveys

Item non-response in household surveys occurs when individuals do not provide answers to specific questions in a survey. The problem is often associated with questions on exact amounts of variables such as income, expenditure, or net worth of some type of assets. Such item non-response may well be nonrandom, implying that the sample of (item) respondents is not representative of the population of interest. This can bias the results of studies that model features of the distribution of the variable that suffers from item non-response, such as its conditional mean or conditional quantiles given a set of covariates. This problem has long been recognized in the economics literature, and is know as the selection problem.

There are several ways to handle this problem. The first is to use as many covariates as possible (X), and to assume that conditional on X, the response process is independent of the variable of interest. This makes it possible to use regression techniques to impute values for non-respondents, leading to, for example, the hot-deck imputation approach. The key element of this approach is that item non-respondents are not systematically different from respondents with the same values of X. See Rao (1996), for an overview of hot-deck imputation, and Juster et al. (1997), for imputation based upon the same assumption in the presence of bracket response.

Since the seminal work by Heckman see (Heckman, 1979, for example), the common view in many economic examples is that the assumption of random item non-response conditional on observed X is unreasonable and can lead to severe selection bias. Instead, a selectivity model is used. This is a joint model of response behaviour and the variable of interest, conditional on covariates. See, for example, the survey of Vella (1998). Parametric and semiparametric selectivity models avoid the assumption of conditional random item non-response, but they do require additional assumptions such as a single index assumption or independence between covariates and error terms.

About ten years ago, a new approach to deal with item nonresponse or selectivity was introduced. See Manski (1989, 1990) and Heckman (1990). This approach does not make any assumptions on the response process. It uses the concept of *identification up to a bounding interval*. Manski (1989) shows that in the presence of item nonresponse, the sampling process alone fails to fully identify most features of the conditional distribution of a variable Y given a vector of covariates, X, but that in many cases, lower and upper bounds for the feature of interest (such as the values of the distribution function of Y given X) can be derived. Manski calls these bounds "worst case bounds." Manski (1994, 1995) shows how these bounds can be tightened by adding nonparametric assumptions on a monotonic relation between Y and non-response or exclusion restrictions on the conditional distribution of Y. Vazquez et al. (1999a) apply several of these bounds to analyze earnings in the Netherlands. Manski (1990), Manski et al. (1992), and Lechner (1999) use them to estimate bounds on treatment effects.

The problem of item non-response can be reduced at the data collection level by, for example, carefully designed surveys, careful coding of responses by the interviewer, reducing question ambiguity, giving guarantees for privacy protection, giving respondents the opportunity to consult tax files, etc. A more direct method to reduce item nonresponse is to include categorical questions to obtain partial information from initial non-respondents. Using categorical questions is often motivated by the claim that certain cognitive factors, such as confidentiality and/or the belief that the interviewer requires an answer that reflects perfect knowledge of the amount in question, can make people more reluctant to disclose information when initially faced with an open-ended question (see, for example, Juster et. al, 1997).

Two types of categorical questions are typically used. In some surveys, initial non-respondent are routed to a range card type of categorical question, where they are asked to choose the category which contains the amount (Y) from a given set of categories. Vazquez et al. (1999b) extend Manski's bounds to incorporate the information from such range card questions, and apply this to savings quantiles, using a household survey for the Netherlands.

An alternative set up for categorical questions is that of unfolding brackets. This is used in well-known US longitudinal studies such as the Panel Study of Income Dynamics (PSID), the Health and Retirement Survey (HRS), and the Asset and Health Dynamics Among the Oldest Old (AHEAD). In this type of design, those who answer 'don't know' or 'refuse' to a question on the specific amount, are asked a question such as *'is the amount $B or more?'*, with possible answers 'yes', 'no', 'don't know', and 'refuse'. They typically get two or three such consecutive questions, with changing bids *$B*: a 'yes' is followed by a larger bid and a 'no' is followed by a smaller bid. Those who answer 'don't know' or 'refuse' on the first bid, are full non-respondents. Those who answer at least one of the bracket questions are called bracket respondents. The latter can be complete or incomplete bracket respondents, depending on whether they answer all the bracket questions presented to them by 'yes' or 'no', or end with a 'don't know' or 'refuse' answer. The advantage of an unfolding bracket design relative to a range card type of question, is that unfolding brackets can elicit partial information on the variable of interest even if the respondent does not complete the sequence, in cases where a range card question might lead to a simple 'don't know' or 'refuse'.

A major problem associated with unfolding brackets is that it may suffer from an anchoring effect (see Jacowitz et al., 1995, and Rabin, 1996, for non-economic examples). A psychological explanation for the anchoring effect is that the bid creates a fictitious believe in the individual's mind: faced with a question related to an unknown quantity, an individual treats the question as a problem solving situation, and the given bid is used as a cue to solve the problem. This can result in responses that are influenced by the design of the unfolding sequence. Hurd et al. (1997) suggest that the anchoring effect can be modeled by assuming that the respondent makes an error when comparing the actual amount (unknown to the respondent) to the bid: instead of comparing Y to B, the respondent compares $Y+\epsilon$ to B. Hurd et al. (1997) assume that ϵ is symmetric around zero and independent of X and Y. They show that the anchoring effect arises if the variance of ϵ decreases for consecutive bracket questions. They estimate a parametric model incorporating this for an experimental module of the AHEAD data, in which respondents are randomly assigned to different starting bids of an unfolding sequence. Their findings support their model and imply strong evidence of anchoring effects.

The Hurd et al. (1997) results imply that answers to unfolding bracket questions may often be incorrect. They also imply that unfolding bracket questions may not give the same answers as range card questions. In the next section, we extended Manski's worst case bounds to account for unfolding bracket questions. We allow for anchoring effects which satisfy a non-parametric assumption implied by the Hurd et al. (1997) framework. We will compare the bounds allowing for the anchoring effect with bounds not allowing for anchoring effects.

3 Theoretical framework

3.1 Worst case bounds; no bracket respondents

We first review Manski's (1989) worst case bounds for the conditional distribution function of a variable Y, at a given $y \in \mathbb{R}$, and given $X = x \in \mathbb{R}^P$. We assume that there is neither unit non-response, nor item non-response on X. We also assume that reported (exact) values of Y and X are correct, and thus exclude under- or over-reporting the value of Y. Let FR indicate that Y is (fully) observed and let NR indicate (full) non-response on Y. $F(y|x)$, the conditional distribution function of Y given $X=x$ in the complete population, can then be expressed as follows.

$$F(y|x) = F(y|x,FR)P(FR|x) + F(y|x,NR)P(NR|x) \qquad \textbf{(1)}$$

The assumptions imply that $F(y|x,FR)$ is identified for all x in the support of X, and can be estimated using, for example, some non-parametric kernel based estimator. The same holds for the conditional probabilities $P(FR|x)$ and $P(NR|x)$. If we assume that, conditional on X, response behavior is independent of Y, then all expressions in the right hand side of (1) would be identified since $F(y|x,FR) = F(y|x,NR)$. This is the assumption of exogenous selection. In general, however, the response behavior can be related to Y, and $F(y|x,NR)$ is not identified, so that $F(y|x)$ is not identified either. Without additional assumptions, all we know about $F(y|x,NR)$ is that it is between 0 and 1. Applying this to (1) gives,

$$F(y|x,FR)P(FR|x) \;\leq\; F(y|x) \;\leq\; F(y|x,FR)P(FR|x) \;+\; P(NR|x) \qquad \textbf{(2)}$$

These are Manski's worst case bounds for the distribution function. The difference between upper and lower bounds is equal to $P(NR|x)$. The narrower the width, the more informative the bounds will be about the unknown distribution function. Thus, a low non-response rate leads to more informative bounds. Additional assumptions can lead to narrower bounds. Examples are monotonicity or exclusion restrictions, see Manski (1994, 1995).

3.2 Partial information from an unfolding bracket sequence

Expressions (1) and (2) do not incorporate information from categorical follow-up categorical questions to initial non-respondents, as discussed in the previous section. Vazquez et al. (1999b) extend the bounds in (2) to account for a range card type of categorical question. They do not allow for anchoring effects which, for well designed range card questions, might not be important. Here, we consider categorical questions in the form of an unfolding bracket sequence. In this subsection, we do not allow for anchoring, but we will do so in the next subsection.

The unfolding brackets design was explained in the previous section. Let *B1* be the initial bid. We assume it is the same for all initial non-respondents, as is the case in the HRS data. Thus the first bracket question is

$$\textit{is the amount } \$B1 \textit{ or more } ? \qquad \textbf{(3)}$$

Individuals can either answer ‘yes’,‘no’ or ‘don’t know’ to this question.[2] Those who answer ‘don’t know’ to this initial bid, become full non-respondents. If the answer to (3) is ‘yes’, individuals get the same question but now with a new bid *B21, with B21>B1*. If the answer is ‘no’, the next bid will be *B20, with B20<B1*. In the HRS, this second question is often the final bracket question, while in some other cases, there is a third question, again with a new bid. We will focus on the case of two bracket questions, leaving more than two questions as a straightforward extension. For the sake of the exposition, we first consider the case where only one bracket question is asked.

3.3 Bounds and unfolding bracket response: One bracket question

In this case, three types of respondents can be distinguished: full respondents (*FR*), bracket respondents (*BR*) and (full) non-respondents (*NR*), so that $F(y|x)$ can be written as

$$F(y|x) = F(y|x,FR)P(FR|x) + F(y|x,BR)P(BR|x) + F(y|x,NR)P(NR|x) \qquad \textbf{(4)}$$

Full respondents answer the initial question and identify $F(y|FR)$, as before. Non-respondents answer ‘don’t know’ to the initial question as well as the bracket question, and, as before, all we know about $F(y|x,NR)$ is that it is between 0 and 1. Bracket respondents report whether $y>B1$ or not.

Define a variable $Q1$ by $Q1=1$ if the answer to (3) is ‘yes’, and 0 if the answer is ‘no’. The the bracket respondents identify $\pi(1|x)=P(Q1=1|x,BR)$. For deriving the bounds, it will be useful to write this as

$$\pi(1|x)=P(Q1=1|Y<B1,x,BR)P(Y<B1|x,BR)+P(Q1=1|Y>B1,x,BR)[1-P(Y<B1|x,BR)] \qquad \textbf{(5)}$$

Not allowing for an Anchoring effect

If there is no anchoring effect, all bracket respondents answer (3) correctly, so that $P(Q1=1|Y<B1,x,BR)=0$ and $\pi(1|x)=1-P(Y<B1|x,BR)$. This leads to the following bounds on $F(y|BR,x)$.

[2] We will not distinguish between the answers ‘don’t know’ and ‘refuse’ and simply write ‘don’t know’.

$$\begin{array}{ll} \text{for} \quad y \le B1 & 0 \le F(y|BR,x) \le [1-\pi(1|x)] \\ \text{for} \quad y > B1 & [1-\pi(1|x)] \le F(y|BR,x) \le 1 \end{array} \tag{6}$$

Combining this with the bounds on *F(y|FR,x)* and *F(NR,x)* yields

$$\begin{array}{c} F(y|FR,x)P(FR|x) \\ \le F(y|x) \le \\ F(y|FR,x)P(FR|x) + [1-\pi(1|x)]P(BR|x) + P(NR|x) \end{array} \tag{7}$$

for $y \le B1$,for $y > B1$,

$$\begin{array}{c} F(y|FR,x)P(FR|x) + [1-\pi(1|x)]P(BR|x) \\ \le F(y|x) \le \\ F(y|FR,x)P(FR|x) + P(BR|x) + P(NR|x) \end{array} \tag{8}$$

The bounds in (7) and (8) will both be sharper than the worst case bounds in (2), as long as there are bracket respondents answering ‘yes’ as well as bracket respondents answering ‘no’.

Allowing for the Anchoring Effect

If responses to (3) are vulnerable to the anchoring effect, (6) is no longer valid, since people may give the wrong answer to (3), so that $P(Q1{=}1|Y{<}B1,x,BR)$ and $P(Q1{=}0|Y{>}B1,x,BR)$ are non-zero. In the Hurd et al. (1997) framework, *Q1* is based upon comparing $Y{+}\epsilon$ to *B1*, where ϵ is the perception error. Hurd et al. (1997) assume that ϵ is normally distributed with zero mean and independent of *Y* and *X*. We will use the weaker (nonparametric) assumption

Assumption A1:

$$\epsilon|(y,x,BR) \ \textit{is distributed with zero median}$$

This assumption implies that the conditional probability that an individual answers correctly is at least 0.5:

$$\begin{array}{l} P(Q1{=}1|Y{<}B1,x,BR) = P(\epsilon \ge B1-Y|B1-Y{>}0,x,BR) \le 0.5 \\ P(Q1{=}1|Y{>}B1,x,BR) = P(\epsilon \ge B1-Y|B1-Y{<}0,x,BR) \ge 0.5 \end{array} \tag{9}$$

Applying (9) to (5) leads to the following bounds on $\pi(1|x)$.

$$\pi(1|x) \leq 0.5P(Y<B1|x,BR) + [1-P(Y<B1|x,BR)]$$
$$\pi(1|x) \geq 0.5[1-P(Y<B1|x,BR)]. \qquad \textbf{(10)}$$

This implies that

$$1-2\pi(1|x) \leq P(Y<B1|x,BR) \leq 2[1-\pi(1|x)]. \qquad \textbf{(11)}$$

This leads to the following bounds on *F(y|BR,x)*.

$$\begin{array}{ll} \text{for } y \leq B1 & 0 \leq F(y|BR,x) \leq 2[1-\pi(1|x)] \\ \text{for } y > B1 & [1-2\pi(1|x)] \leq F(y|BR,x) \leq 1 \end{array} \qquad \textbf{(12)}$$

This implies either a non-trivial lower bound or a non-trivial upper bound for all $\pi(1|x)$ not equal to 0.5. If $\pi(1|x)<0.5$, not too many people will have a high *Y*, since by assumption at least half of the people with high *Y* will answer *Q1=1.* This leads to a lower bound on $F(y|BR,x)$. If on the other hand, $\pi(1|x)>0.5$, not too many people will have a low *Y*, since by assumption at least half of the people with low *Y* will answer *Q1=0.* This leads to an upper bound on $F(y|BR,x)$. Replacing (6) by (12) and applying this to (4) leads to the following bounds on *F(y|x)*:

for $y \leq B1$

$$\begin{gathered} F(y|FR,x)P(FR|x) \\ \leq F(y|x) \leq \\ F(y|FR,x)P(FR|x) + 2[1-\pi(1|x)]P(BR|x) + P(NR|x) \end{gathered} \qquad \textbf{(13)}$$

for $y > B1$,

$$\begin{gathered} F(y|FR,x)P(FR|x) + [1-2\pi(1|x)]P(PR|x) \\ \leq F(y|x) \leq \\ F(y|x,FR)P(FR|x) + P(PR|x) + P(NR|x) \end{gathered} \qquad \textbf{(14)}$$

These bounds are sharper than Manski's worst case bounds in (2) (unless *P(BR|x)=0* or

$\pi(1|x)=0.5$). On the other hand, they are wider than the bounds in (7)-(8), which were constructed under the stronger assumption of no anchoring.

3.4 More than one unfolding bracket question

With two unfolding bracket questions, those who answer 'yes' to question (3) are given a second question with bid *B21*, where *B21>B1*, and those who answer 'no' get a second question with *B20*, where *B20<B1*. Again, they can answer 'yes', 'no' or 'don't know'. In this subsection we assume that every bracket respondent answers the second question with 'yes' or 'no', so that all bracket respondents complete the unfolding sequence. This will be generalized below.

Not allowing for an anchoring effect

If we assume that all those who answer the bracket questions answer them correctly, then we know for all bracket respondent which of the four categories [0, *B20*], [*B20, B1*],[*B1, B21*] and [*B21*, ∞] contains their value of *y*. The information is the same as the information provided by a range card question with the same four categories. Bounds on $F(y|x)$ for this case are given in Vazquez et al. (1999b). They are a straightforward generalization of the bounds in (7) and (8). Denoting the category containing y by *[L(y), U(y)]* (for example, for *B20<y<B1*, *L(y)=B20* and *B(y)=B1*, etc.), the bounds on *F(y|BR,x)* are given by

$$\begin{gathered} F(L(y)|BR,x) \leq F(y|PR,x) \leq F(U(y)|BR,x) \\ \textit{and} \\ 0 \;\leq\; F(y|NR,x) \;\leq\; 1 \end{gathered} \tag{15}$$

Combining this with (4) leads to the following bounds on *F(y|x)*.

$$\begin{gathered} F(y|FR,x)P(FR|x) \;+\; F(L(y)|BR,x)P(BR|x) \\ \leq\; F(y|x) \;\leq \\ F(y|FR,x)P(FR|x) \;+\; F(U(y)|BR,x)P(BR|x) \;+\; P(NR|x) \end{gathered} \tag{16}$$

The width between the upper and lower bound for given *x* is equal to

$$P(NR|x) \;+\; P(BR|x)[F(U(y)|BR,x) - F(L(y)|BR,x)] \tag{17}$$

This is generally smaller than the width of Manski's worst case bounds in (2), *P(NR|x)+P(BR|x)*, which do not use the bracket information.

Allowing for the Anchoring Effect

Define a dummy variable *Q2* by *Q2=1* if the answer to the second bracket question is 'yes', and *Q2=0* if it is 'no'. Define $\pi(2{,}0|x)=P(Q2=1|Q1=0,x,BR)$ and $\pi(2{,}1|x)=P(Q2=1|Q1=1,x,BR)$. These two probabilities, together with $\pi(1|x)=P(Y>B1|x,BR)$ defined above, are identified by the answers of the bracket respondents. Extending (5) gives

$$
\begin{aligned}
\pi(1|x) &= P(Q1=1|Y<B1,x,BR)P(Y<B1|x,BR) \\
&\quad + P(Q1=1|Y>B1,x,BR)P(Y>B1|x,BR) \\
\pi(2{,}0|x) &= P(Q2=1|Y<B20,Q1=0,x,BR)P(Y<B20|Q1=0,x,BR) \\
&\quad + P(Q2=1|Y>B20,Q1=0,x,BR)P(Y>B20|Q1=0,x,BR) \\
\pi(2{,}1|x) &= P(Q2=1|Y<B21,Q1=1,x,BR)P(Y<B21|Q1=1,x,BR) \\
&\quad P(Q2=1|Y>B21,Q1=1,x)P(Y>B21|Q1=1,x,BR)
\end{aligned}
\tag{18}
$$

Generalizing the Hurd et al. (1997) framework, we model incorrect answers to all three bracket questions by introducing errors ϵ_1 , $\epsilon_{2,0}$ and $\epsilon_{2,1}$: *Q1=1* if $Y+\epsilon_1>B1$; if *Q1*=01 then *Q2*=1; if $Y+\epsilon_{2,0}>B20$, and if *Q1=1* then *Q2*=1 if $Y+\epsilon_{2,1}>B21$. Hurd et al. (1997) assume that ϵ_1, $\epsilon_{2,0}$ and $\epsilon_{2,1}$ are independent of each other and of *X* and *Y*, and are normally distributed with zero means. The anchoring effects in their data can be explained if $\epsilon_{2,0}$ and $\epsilon_{2,1}$ have smaller variance than ϵ_1. We do not need this. All we need is the following generalization of Assumption A1.

Assumption A2:

$$\epsilon|(y,x,BR),\ \epsilon|(y,x,BR,Q1=0)\ \textit{and}\ \epsilon|(y,x,BR,Q1=1)\ \textit{have zero median}$$

This is much weaker than the assumptions of Hurd et al. (1997). It implies that each bracket question is answered correctly with probability at least 0.5:

$$
\begin{aligned}
P(Q1=1|Y<B1,x,BR) &\le 0.5; & P(Q1=1|Y<B1,x,BR) &> 0.5 \\
P(Q2=1|Y<B20,Q1=0,x,BR) &\le 0.5; & P(Q2=1|Y>B20,Q1=0,x,BR) &> 0.5 \\
P(Q2=1|Y<B21,Q1=1,x,BR) &\le 0.5; & P(Q2=1|Y>B21,Q1=1,x,BR) &> 0.5
\end{aligned}
\tag{19}
$$

Together with (18), (19) implies the following bounds for bracket respondents:

$$
\begin{aligned}
&[1-2\pi(1|x)] \;\le\; P(Y<B1|x,BR) \;\le\; 2[1-\pi(1|x)] \\
&[1-2\pi(2,0|x)] \;\le\; P(Y<B20|Q1=0,x,BR) \;\le\; 2[1-\pi(2,0|x)] \\
&[1-2\pi(2,1|x)] \;\le\; P(Y<B21|Q1=1,x,BR) \;\le\; 2[1-\pi(2,1|x)]
\end{aligned}
\tag{20}
$$

This leads to the following bounds on $F(y|x,BR)$ and $F(y|x)$.

For y in [0, *B20*]:

$$
0 \;\le\; F(y|BR,x) \;\le\; \min[2(1-\pi(1|x)),2(1-\pi(2,0|x)),2(1-\pi(2,1|x))] \tag{21}
$$

and with (4),

$$
\begin{gathered}
F(y|FR,x)P(FR|x) \\
\le\; F(y|x) \;\le \\
F(y|FR,x)P(FR|x) \;+\; P(NR|x) \\
+\; \min[2(1-\pi(1|x)),2(1-\pi(2,0|x)),2(1-\pi(2,1|x))]P(BR|x).
\end{gathered}
\tag{22}
$$

For y in [*B20, B1*],

$$
[1-2\pi(2,0|x)] \;\le\; F(y|BR,x) \;\le\; \min[2(1-\pi(1|x)),2(1-\pi(2,1|x))]P(BR|x) \tag{23}
$$

and

$$
\begin{gathered}
F(y|FR,x)P(FR|x)+[1-2\pi(2,0|x)]P(BR|x) \\
\le\; F(y|x) \;\le \\
F(y|FR,x)P(FR|x) \;+\; \min[2(1-\pi(1|x)),2(1-\pi(2,1|x))]P(BR|x) \;+\; P(NR|x).
\end{gathered}
\tag{24}
$$

For y in [*B1, B21*],

$$
\max[(1-2\pi(1|x)),(1-2\pi(2,0|x))] \;\le\; F(y|BR,x) \;\le\; 2[1-\pi(2,1|x)] \tag{25}
$$

and

$$F(y|FR,x)P(FR|x) \; + \; \max[(1-2\pi(1|x)),(1-2\pi(2,0|x))]P(BR|x)$$
$$\leq F(y|x) \leq \tag{26}$$
$$F(y|FR,x)P(FR|x) \; +2[1-\pi(2,1|x)]P(BR|x) \; + \; P(NR|x).$$

For y in [*B21*, ∞],

$$\max[(1-2\pi(1|x)),(1-2\pi(2,0|x)),(1-2\pi(2,1|x))] \; \leq \; F(y|BR,x) \; \leq \; 1 \tag{27}$$

and

$$F(y|FR,x)P(FR|x) \; + \; \max[(1-2\pi(1|x)),(1-2\pi(2,0|x)),(1-2\pi(2,1|x))]P(BR|x)$$
$$\leq \; F(y|x) \; \leq \tag{28}$$
$$F(y|FR,x)P(FR|x) \; + \; [1-P(FR|x)].$$

The bounds in (22), (24), (26) and (28) take into account the possibility that responses to an unfolding bracket can be affected by the anchoring effect. Therefore these bounds are wider than the bounds in (16), which are derived under the assumption of no anchoring effects. On the other hand, the bounds in (22), (24), (26) and (28) are narrower than Manski's worst case bounds in (2).

3.5 Complete and incomplete bracket respondents

As in the previous subsection, we consider the case where at most two bracket questions are asked. Until now we assumed that all bracket respondents complete the unfolding bracket sequence. In practice, however, some of them answer 'don't know' to the second bracket question. Thus we can distinguish two types of bracket respondents: those who answer both questions with 'yes' or 'no' (CBR, complete bracket respondents), and those who only answer one question with 'yes' or 'no' (IBR, incomplete bracket respondents). We do not make any assumptions on the relation between response behavior and value of *Y*, so we allow for the possibility that incomplete bracket respondents are a selective sub-sample of all bracket respondents.

The conditional distribution function for bracket respondents can now be written as follows.

$$F(y|BR,x) = F(y|CBR,x)P(CBR|BR,x) + F(y|IBR,x)P(IBR|BR,x) \tag{29}$$

P(CBR|BR,x) and *P(IBR|BR,x)* are both identified, since it is observed whether bracket respondents are complete or incomplete bracket respondents. Bounds on *F(y|CBR,x)* can be derived as in Section 3.4, using complete bracket respondents only. Bounds on *F(y|IBR,x)* can be derived as in Section 3.3, using incomplete bracket respondents only. Combining these and plugging them into (29) leads to bounds on *F(y|BR,x)*. As before, two sets of bounds can be derived, allowing or not allowing for anchoring. The bounds on *F(y|BR)* can be combined with *F(y|FR,x)* and bounds on *F(y|NR,x)* in the same way as before, and thus yield bounds on *F(y|x)*. Note that this procedure treats complete and incomplete bracket respondents separately, and does not impose any relation between the distribution of Y in these two sub-populations.

3.6 Bounds on Quantiles

Distributions for variables like income, savings, etc., are often described in terms of (conditional) quantiles. For $\alpha \in [0,1]$, the α-quantile of the conditional distribution of *Y* given *X=x,* is the smallest number $q(\alpha,x)$ that satisfies $F_Y[q(\alpha,x)] \geq \alpha$:

$$q(\alpha,x) \equiv inf \ \{y: F(y|x) \geq \alpha\} \tag{30}$$

For α >1, we set $q(\alpha,x) = \infty$, and for α <0, $q(\alpha,x) = -\infty$. Following Manski (1994), bounds on these quantiles can be derived by 'inverting' the bounds on the distribution function. All the bounds in Sections 3.1-3.5 can be written as

$$lb(y,x) \leq F(y|x) \leq ub(y,x) \tag{31}$$

for appropriate choices of *lb(y,x)* and *ub(y,x),* all of them non-decreasing functions of *y*. Inverting this gives the following bounds on the quantiles:

$$inf \ \{y: lb(y,x) \geq \alpha\} \geq inf \ \{y: F(y|x) \geq \alpha\} \geq inf \ \{y: ub(y,x) \geq \alpha\} \tag{32}$$

Plugging in the bounds in the previous subsections, yields bounds on the conditional quantiles of *Y*. This is easily illustrated using a graph of the distribution function, with *y* along the horizontal axis and $F(y|x)$ along the vertical axis. The bounds on the distribution function squeeze $F(y|x)$ in between two curves; the vertical distance between these two curves is the width between the bounds (at each given value of y). Reading the same graph horizontally gives, for a given probability value $\alpha \in [0,1]$, a lower and upper bound on the α-quantile.

4 The Data

The data we use comes from the 1996 wave of the Health and Retirement Survey (HRS). This survey is a longitudinal study conducted by the University of Michigan on behalf of the American Institute of Aging. It focuses mainly on aspects of health, retirement and economic status of USA citizens born between 1931 and 1941. For this purpose, the study collects individual and household information from a representative sample of the USA population from this cohort. The data is collected every two years, with the first wave conducted in the summer of 1992.

Initially the panel consisted of approximately 7,600 households. The respondents are the members of the household that fulfil the age criteria (the household representative) and their partners, regardless of age (second household respondent). This leads to approximately 12,600 individual respondents in the first wave of the panel. Each respondent answers individually to questions on health and retirement issues. The household representative also answers questions on past and current income and pension plans (including those of his or her partner), as well as questions at household level, e.g. on housing conditions, household assets and family structure. If health problems prevent the household representative from answering these questions, someone else (e.g. the spouse) will answer on their behalf. All interviews are conducted over the telephone, unless the household has no telephone, or health reasons prevent either representative or spouse answering over the telephone, in which case the interviewer will visit the household. The survey is meant to be carried out over a period of 10 years. If respondents die, they are replaced by a remaining household member. This reduced attrition in the panel.

The 1996 wave recorded data from 6,739 households, covering 10,887 individuals. In 4,148 of these households, two respondents gave interviews. The remaining 2,591 are single respondent households. Table 1 shows sample statistics for some background variables. The first column refers to the full sample. The second and third column refer to the sub-samples of household representatives and second household respondents. The statistics show that 51% of the household representatives are women, while only 62% of second household respondents (usually the spouse) are women. There is little difference between educational achievement of household representatives and second household respondents.

The shares of Whites, Blacks and Hispanics reflect the ethnic composition of the cohorts in the sample. About 62% of the respondents participate in the labor market, most of them are employees. Approximately 80% of the households in the sample are home owners.

The 1996 wave of the HRS panel groups all variables in 11 subsets and a supplement that consists of experimental modules (mostly to check the consistency of answers to previous questions). In the subset, named ‘Assets and Income’, the household representatives provide information about their own incomes, their partner’s incomes, household savings, and various other types of net wealth. We will apply the bounds of Section 3 to the variable ‘wages and salaries of the household representative’. This variable shows a significant percentage of initial non-respondents who, subsequently, are routed to an unfolding bracket sequence where they can disclose partial information on the missing variable.

Table 1: Means (standard deviation) and Percentages (standard errors) for some background variables for the 1996 wave of the HRS panel.

	All Units	Household Representatives	Second Household Respondent
Number of Observations	**10,887**	**6,739**	**4,148**
Age	59.6 (5.62)	60.7 (5.07)	58.6 (6.41)
Percentage Males	45 (0.5)	49 (0.6)	38 (0.8)
Education [1]	2.32 (1.02)	2.36 (1.03)	2.25 (0.98)
Percentage home owners	-	79 (0.5)	-
Percentage Whites	71 (0.4)	69 (0.6)	76 (0.7)
Percentage Hispanics	9 (0.3)	8 (0.3)	11 (0.5)
Percentage Black [2]	16 (0.4)	19 (0.5)	9 (0.4)
Other races	4 (0.2)	4 (0.3)	4 (0.3)
Percentage employed	62 (0.5)	62 (0.6)	64 (0.7)
For wages only	47 (0.5)	46 (0.6)	50 (0.8)
Self-employment only	0.09 (0.003)	0.08 (0.003)	0.10 (0.005)
For wages & self-emp.	0.06 (0.002)	0.08 (0.003)	0.04 (0.003)

Notes:

1. Education: educational achievement on a scale of 1 to 4; 1: has completed primary education (up to the 10^{th} grade in the USA education system), 2: has completed high school (up to the 12^{th} grade); 3: some form of college or post-high school education; 4: has completed at least a first degree at university level.
2 This group are those who describe themselves as black African-American.

Wages and salaries of the household representative

All household representatives are asked to provide information on employment status and earned incomes for themselves and their partners. Initially, each household representative is asked if he or she worked for pay during the last calendar year. To this question, 4,145 individuals answered 'yes', 2,097 individuals answered 'no', and the remaining 497 answered 'don't know' or 'refuse'. Each of the 4,145 who answered 'yes' are asked to specify if any of their earnings during the last calendar year came from self-employment, wages and salaries, or a combination of these two sources: 3,608 individuals declared that all (or some) of their earnings came from wages and salaries. These individuals are asked the following question.

> *'About how much wages and salary income did you receive during the last calendar year?'*
>
> *1 - 'any amount' (in USA dollars)*
> *'Don't know'*
> *'Refuse'*

3,160 individuals answered the above question with an exact amount in USA dollars, ranging from \$ 0,00 to \$350,000, with a mean of \$29,430 and standard deviation \$26,430. The median was \$25,000. The remaining 448 individuals answered 'don't know' or 'refuse', implying a 12.4% initial non-response rate. This latter group was routed to a sequence of unfolding bracket questions, with starting bid *B1*=\$25,000. At this initial stage of the unfolding sequence, 119 individuals answered 'don't know' or 'refuse'. Thus the full non-response rate is 3.3%. The remaining 329 individuals form the sample of bracket respondents.

For this 'wages and salaries' variable, the unfolding sequence consists of two questions. Those who answered 'yes' to the initial bid of \$25,000 were routed to a second question with bid *B21*=\$50,000, whereas those who answered 'no' were routed to a question with bid *B20*=\$5,000. In each case, the question is the same as that given in (3) - only the bid changes. At the second question of the unfolding sequence, individuals can again answer 'don't know' or 'refuse'. Those who do this are 'Incomplete bracket respondents'. For this particular variable, 320 individuals completed the sequence of unfolding brackets, while the remaining 9 bracket respondents are incomplete bracket respondents.

Table 2 shows some sample statistics for the sample of individuals with nonzero wages and salaries, partitioned by response behavior. Comparing the first columns of Table 1 and Table 2 shows that the individuals who received wages and salaries are, on average, similar to the complete sample in terms of age, gender, home ownership and ethnicity. The sub-sample of bracket respondents contains a larger percentage of females than the other samples. Likewise, people in this sub-sample have lower educational achievement, are less likely to own their home, and are less often white. The statistics of the sub-group of incomplete bracket respondents differ

Table 2: Means (standard deviations) and Percentages (standard errors) for some background variables: Sample of respondents who received wages and salaries in the past calendar year

	All employed with wages	**Full Respondents (FR)**	**Bracket Respondents (BR)**		**Full Non-respondents (NR)**
			Complete bracket respondents (CBR)	**Incomplete bracket respondents (IBR)**	
Number of Observations	**3602**	**3160**	**320**	**9**	**113**
Average age	58.6 (4.7)	58.6 (4.7)	58.8 (4.7)	55.7 (3.2)	59 (4.9)
Percentage Males	50 (0.8)	52 (0.9)	38 (2.7)	0.78 (0.14)	0.45 (4.7)
Education [1]	2.52 (1.01)	2.6 (1.03)	2.2 (1.02)	3.1 (1.01)	2.6 (0.99)
% Home owners	73(0.7)	74(0.8)	65(2.7)	89(10.0)	83(3.5)
% White	72 (0.7)	75 (0.8)	58 (2.8)	78 (14)	72 (4.2)
% Hispanics	8 (0.5)	7 (0.5)	9 (1.6)	0(0)	5 (2.1)
% Black [2]	18 (0.6)	16 (0.7)	32 (2.6)	12 (11)	21 (3.8)
% Other races	2 (0.2)	2 (0.3)	2 (0.8)	10 (10)	3 (1.6)

1,2: see Notes Table 1

substantially from those of the other groups, but this is based upon very few observations.

5 Estimates of the Bounds

In this section we apply the various upper and lower bounds on distribution functions and quantiles derived in Section 3 to the variable wages and salaries of the household representative, as described in Section 4. First, we use the full sample, not conditioning on any covariates. In addition, we estimate the bounds for males and females separately (i.e., conditioning on gender), and use these results to determine whether significant differences in the quantiles between the genders can be detected.

Since we only condition on discrete variables, we do not need non-parametric smoothing techniques, and our estimates can be computed as functions of fractions in the (sub-)sample satisfying a given condition.

The width between point estimates of upper and lower bounds reflect the uncertainty due to item nonresponse. We also estimate confidence bands around the estimated upper and lower bounds, to measure uncertainty due to sampling error. For all sets of bounds, these confidence bands are estimated using a bootstrap method, based on 500 (re-)samples drawn with replacement from the original data. The lower and upper bound are estimated 500 times, and the confidence bands are formed by the 2.5% and 97.5% percentiles in these 500 estimates. This results in a two-sided 95% confidence bands for both the upper and lower bound. In the figures below we report the lower confidence band for the lower bound and the upper confidence band for the upper bound. The (vertical) distance between these thus reflects both the uncertainty due to sampling error and the uncertainty due to item non-response.

5.1 Bounds using the full sample

Figure 1 shows estimates of Manski's (1995) worst case bounds, not using the bracket response information. The solid curves are the estimated upper and lower bounds, whereas the dashed curves are the estimated confidence bands. The horizontal distance between the upper and lower bound equals 0.124, the initial percentage of item non-response. Table 3 shows point estimates and confidence intervals for a selection of quantiles corresponding to Figure 1. For example, with at least 95% confidence, the median of respondent's wages and salaries is between \$19,500 and \$29,000. From this table, and Figure 1, we can conclude that, due to the initial percentage of item nonresponse, the width between upper and lower bound is quite large, and seem hardly useful to draw economically meaningful conclusions.

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Table 3: Estimated bounds and confidence intervals on Respondent's wages and salaries (in US$). Worst case bounds without bracket information (cf. Figure 1)

Quantiles	**Confidence interval (Lower)**	**Lower bound**	**Upper bound**	**Confidence interval (Upper)**
25th Percentile	$5,800	$7,700	$13,700	$14,700
40th Percentile	$13,700	$14,700	$22,500	$24,500
50th Percentile	$19,500	$20,800	$27,900	$29,900
60th Percentile	$25,000	$26,000	$34,600	$37,000
75th Percentile	$35,600	$36,900	$50,000	$55,000
90th Percentile	$51,000	$55,000	$350,000	max

Our next step is to estimate the extended version of the bounds incorporating the information provided by the bracket respondents. Table 4 summarizes the information provided by these 329 respondents.

Table 4: Information on Respondent's wages and salaries provided by bracket respondents

Group	**Bid 1: B1**	**answer**	**Bid 2: B21/B20**	**answer**	**Resulting bracket bounds**	**Number**
				Yes	**$50,000 — max**	30
		Yes	> $50,000 ?	No	**$25,000 — $50,000**	86
CBR	>$25,000 ?					
		No	> $ 5,000 ?	Yes	**$5,000 — $25,000**	170
				No	**$0 — $5,000**	34
		Yes	> $50,000 ?	DK, RF.	**> $25,000**	9
IBR	>$25,000 ?					
		No	> $ 5,000 ?	DK, RF.	**< $25,000**	0

Bounds accounting for bracket information can allow for an anchoring effect, or not. To illustrate the difference, we first present estimates for the upper and lower bounds for the distribution function of bracket respondents only, F(y|BR). Figure 2 shows the estimates of the bounds according to expression (15), assuming there is no anchoring effect. Figure 3 on the other hand is based on estimating expressions (21), (23), (25) and (27), allowing for the anchoring effect and using Assumption A2. Comparing Figure 2 to Figure 3 shows that allowing for the anchoring effect substantially reduces the information provided by bracket respondents.

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Figures 4 and 5 show the results concerning the distribution of Respondents wages and salaries in the complete population, combining the estimates for full-respondents and the bounds for full non-respondents with Figures 2 and 3, respectively.

The interpretation of the curves in both cases is the same as in Figure 1. Comparing the width between the bounds in either Figure 4 or Figure 5 to that in Figure 1 shows that including the bracket information greatly improves the information content of the bounds. Figure 4 obviously does a better job than Figure 5 in this respect, but at the cost of adding the assumption of no anchoring.

Table 5 illustrates these findings in more detail by comparing the 95% confidence intervals in these two figures. For example, the third row shows that when the bounds are estimated without allowing for the anchoring effect, the median is bounded between $21,000 and $25,900. If we allow for the anchoring effect, the median is between $19,500 and $27,900. Both intervals are smaller than the 'worst case' interval in Table 1, ($19,500; $29,900), which does not use the bracket information at all.

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Table 5: Confidence Intervals for quantiles of Respondent's wages and salaries, allowing and not allowing for anchoring (cf. Figure 4 and Figure 5.

Quantiles	**Point estimates**	**Point estimates (based on 95% confidence), no anchoring effect (Figure 4).**	**Point estimates (based on 95% confidence), with anchoring effect (Figure 5)**
25th Percentile	**Lower bound:**	$7,900	$6,700
	Upper bound:	$14,700	$14,700
	Difference:	**$6,800**	**$8,000**
40th Percentile	**Lower bound:**	$15,800	$14,400
	Upper bound:	$23,400	$23,900
	Difference:	**$7,600**	**$9,500**
50th Percentile	**Lower bound:**	$21,000	$19,500
	Upper bound:	$25,900	$27,900
	Difference:	**$4,900**	**$8,400**
60th Percentile	**Lower bound:**	$25,000	$25,000
	Upper bound:	$31,500	$35,000
	Difference:	**$6,500**	**$10,000**
75th Percentile	**Lower bound:**	$35,600	$35,600
	Upper bound:	$47,950	$50,000
	Difference:	**$12,350**	**$14,400**
90th Percentile	**Lower bound:**	$52,540	$52,540
	Upper bound:	$70,000	max
	Difference:	**$17,460**	**undefined**

5.2 Separate Estimates higher and lower education

Until now we have used the full sample of households representative who declared to earn wages and salaries. In this section, we distinguish between individuals who have achieved a basic level of education (up to high school) and those who have a higher level of education (attended college/technical college beyond high school and/ or attended university). The purpose is to use the estimates of the bounds to test for significant difference between the earnings of these two populations. The percentage of individuals declaring to earn some form of wages and salaries is similar between the two populations, but initial nonresponse rate is slightly higher for low educated than high educated (13.4% vs. 10.9%), although the picture changes once nonresponse individuals are allowed to provide information with a categorical question, since full nonresponse is higher for high educated than low educated (3.7% vs. 2.3%). This could be explain, for example, by suggesting that once initial non-respondents are allowed to provide some information with a categorical question, confidentiality, rather than lack of accurate information, will be the dominant factor that will determine the nonresponse rate, assuming that higher earners (high educated) are more reluctant to disclose information (see Vazquez et al. (1999b)).

Table 6: Sample statistics and response behavior by level of education of household respondent, for variable wages and salaries.

	All	Low education	High education
Number of Observations in the survey	6,739	4,110	2,629
Units with incomes	3,602	1,978	1,624
Number of full respondents	3,160 (88%)	1,713 (86.6%)	1,447 (89.1%)
Mean (std. Deviation)	\$29,430 (\$26,430)	\$22,813 (\$18,080)	\$38,298 (\$31,765)
Median	\$25,000	\$19,000	\$33,000
Number of initial non-respondents	442 (12.3%)	265 (13.4%)	177 (10.9%)
Number of bracket respondents	329 (9.1%)	212 (10.7%)	117 (7.2%)
Number of full non respondents	113 (3.1%)	53 (2.3%)	60 (3.7%)

Figures 6 and 7 show estimates of Manski's basic worst case bounds for low educated and high educated, respectively. They are constructed in the same way as Figure 1: the solid curves are the estimated upper and lower bounds, and the dashed curves are the confidence bands. The bounds for low educated are wider than those for high educated, due to the higher nonresponse rate. Figure 8 compares the regions of identification for the unknown quantiles of the distribution for low educated (solid curves) and high educated (dashed curves).

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Except in the upper tails of the distribution, the upper and lower bounds on the quantiles for the high educated population are above those of the low educated population. Up to the 30^{th} percentile, the upper bound for the low educated is above the lower bound for the high educated, so that there is not enough evidence to suggest that for these percentile range high educated are higher earners than low educated. The same holds for the percentiles above the 80^{th} percentile. On the other hand, there is no overlap for percentiles between the 30^{th} and 80^{th}. Thus, an informal test of the null hypothesis that one of these percentiles is the same for both populations, would lead to rejection.

The result of formal tests for selected quantiles are presented in Table 7. The final column gives the t-values of the difference between the estimated lower bound for high educated and the estimated upper bound for the low educated, based upon the number in the columns[3] . The one sided t-test rejects equality for all the percentiles above the 30^{th} percentile and up to the 90^{th} percentile.

3

The test statistic is $((Q_{high} - Q_{low})/\Delta)$, where Q_{high} is the lower bound point estimate for high educated and Q_{low} is the upper bound point estimate for the low educated. Δ is the estimated standard deviation of $(Q_{high} - Q_{low})$, i.e., $\Delta=(\hat{\sigma}^2_{high}+\hat{\sigma}^2_{low})^{(1/2)}$ where $\hat{\sigma}^2_{high}$ and $\hat{\sigma}^2_{low}$ are th bootstrap estimates of the variances of the estimates for Q_{high} and Q_{low} . (These variances are estimated by re-sampling 500 times from the original data, with replacement, and estimating the variance of these 500 estimates).

Table 7: Tests for differences between selected quantiles for high educated and low educated based on Manski's worst case bounds without bracket respondents. (variable wages and salaries)

	Low edu (Upper bound) st. error	**Low edu (Upper bound) point estimate**	**High edu (Low bound) point estimate**	**High edu (Low bound) st. error**	**test statistic (one sided t-test)**
20th Percentile	$365	$9,800	$6,800	$815	-3.36
25th Percentile	$413	$11,900	$9,800	$1,074	-1.83
30th Percentile	$521	$13,000	$14,700	$1,066	1.43
40th Percentile	$429	$17,900	$23,900	$1,186	4.76
50th Percentile	$572	$22,500	$30,000	$754	7.92
60th Percentile	$844	$27,400	$35,600	$942	6.48
75th Percentile	$1,089	$39,400	$48,600	$945	6.38
80th Percentile	$1,575	$46,700	$52,500	$1,712	2.49
90th Percentile	$2,130	$350,000	$60,000	$1,560	-109.84

Next, we want to see if including the information provided by bracket respondents affects the above conclusion. The first step is to examine the bounds on the quantiles in the sub-population of bracket respondents, allowing and not allowing for anchoring (cf. Figures 2 and 3). These are presented in Figures 9 and 10 for low educated, and Figures 11 and 12 for high educated.

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For both high and low educated, the results are similar to those for the whole sample, illustrated in Figure 2 and 3, although allowing for anchoring (Figures 10 and 12) in separate populations leads to much less informative bounds than allowing for anchoring with the full sample (Figure 3). Combining this with the information for the full respondents gives the bounds on the quantiles for the two populations, presented in Figures 13 and 14 (low educated) and Figures 15 and 16 (high educated). This bounds are narrower than those in Figures 6 and 7.

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Figure 17 compares the confidence bands for low and high educated if anchoring is not allowed for (drawn from Figures 13 and 15). Table 8 presents the results of formal tests for equality on earnings of selected quantiles for these two populations. Figure 18, associated with Table 9, does the same but now allowing for an anchoring effect. In both cases, comparing Table 7 to Tables 8 and 9 allowing or not for anchoring, the bracket information is much more informative since the null of equality is rejected from the 30^{th} percentile of the distribution. Thus, whether we allow or not for anchoring the power of the test will increase relative to that based on Manski's basic worst case bounds.

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Table 8: Tests for differences between selected quantiles for high educated and low educated based on Manski's worst case bounds with bracket respondents: no anchoring (variable wages and salaries)

	Low edu (Upper bound) st. error	**Low edu (Upper bound) point estimate**	**High edu (Low bound) point estimate**	**High edu (Low bound) st. error**	**test statistic (one sided t-test)**
20th Percentile	$533	$8,900	$7,700	$860	-1.19
25th Percentile	$572	$10,800	$10,700	$1,020	-0.09
30th Percentile	$378	$12,750	$16,700	$813	4.41
40th Percentile	$545	$17,500	$25,000	$139	13.33
50th Percentile	$615	$22,000	$30,000	$678	8.74
60th Percentile	$545	$25,000	$37,000	$1,110	9.70
75th Percentile	$986	$31,500	$49,500	$437	16.69
80th Percentile	$1,033	$37,000	$52,500	$1,680	7.86
90th Percentile	$1,820	$50,000	$66,000	$1,465	6.85

Table 9: Tests for differences between selected quantiles for high educated and low educated based on Manski's worst case bounds with bracket respondents: anchoring (variable wages and salaries)

	Low edu (Upper bound) st. error	**Low edu (Upper bound) point estimate**	**High edu (Low bound) point estimate**	**High edu (Low bound) st. error**	**test statistic (one sided t-test)**
20th Percentile	$358	$9,800	$7,700	$835	-2.31
25th Percentile	$425	$12,000	$12,000	$1,114	0.00
30th Percentile	$515	$13,000	$15,800	$1,202	2.14
40th Percentile	$409	$17,900	$25,000	$903	7.16
50th Percentile	$618	$22,500	$30,000	$791	7.47
60th Percentile	$146	$25,000	$35,600	$952	11.01
75th Percentile	$1,111	$34,600	$48,600	$880	9.88
80th Percentile	$1,208	$40,000	$52,600	$1,688	6.07
90th Percentile	$3,320	$52,500	$66,000	$1,465	3.72

6 Conclusions

In this paper we have extended the Manski's approach to deal with item nonresponse in survey data. Manski's approach consists of estimating a bounding interval around the parameter of interest, such as a conditional quantile. The approach allows for selective item non-response and avoids the type of assumptions usually associated with parametric and semi-parametric methods.

On the other hand, it does not fully identify the unknown parameters, but only an upper and a lower bound. We extend these bounds to take into account that initial non-respondents can provide partial information by answering follow up categorical questions. Nowadays, many household surveys rely on unfolding sequence type of categorical questions to reduce the percentage of item nonresponse. Hurd et al. (1997) have shown that responses to such questions, on variables like income, consumption or savings, can be subject to a psychometric bias known as the anchoring effect: the answer is affected by the wording in the questions and thus can suffer from response errors. Hurd et al. (1997) model this response error with a parametric set up. We compare extensions on Manski's worst case bounds which do and do not allow for this anchoring effect. In the latter case, our assumptions on the nature of the anchoring effect are more general than those of Hurd et al. (1997). Using the variable wages and salary of the household representative taken from the 1996 wave of the Household and Retirement Survey, we compare estimates of Manski's basic worst case bounds with estimates of our extended bounds.

For the variable that we consider, the initial nonresponse rate is 12.4%. Most of these initial non-respondents answer some unfolding bracket questions, and the percentage of full non-response is only 3.3%. Since the distance between upper and lower bounds is driven by the percentage of item non-response, we find that incorporating information provided by bracket respondents tightens the bounds. If we allow for anchoring effects, however, the gain in information is much smaller than under the assumption of no anchoring.

We also use the bounds to test for equality of quantiles of low and high educated household representatives, and use these bounds to test for equality on earning between these two populations. According to Manski's basic worst case bounds, from the 40th to 80th percentiles high educated are significantly higher earners than low educated household representatives, although the null of equality cannot be rejected for percentiles in the tails of the distribution. Adding the information provided by bracket respondents improves the power of the tests under both allowing and not allowing for the anchoring assumption, and leads to rejecting the null more often. Since allowing for anchoring leads to less informative bounds than not allowing for it, the power of the test with bracket respondents and anchoring, although improving, is similar in power with respect If the anchoring effect is allowed for, however, the results are similar to the use of worst case bounds with no bracket information.

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