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Explaining the Size and Nature of Response in a Survey on Health Status and Economic Standard

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Using rich register data to analyze response behavior in a survey on health and economic standard, a model to explain contact and participation probabilities is estimated. A main result is that both probabilities are lower among respondents who are less well-off, out of the labor market, on benefits or immigrants. We also find a significant time-cost effect on participation. Previous findings that the probability of contact is low in urban areas and among singles are confirmed.

Key words: Nonresponse; response process; probit with selection; JEL-classification C34, C42, J14.

1. Introduction and Motivation

Nonresponse is probably the most severe problem in survey research. Today it is not unusual to find surveys with a response rate even below 50 percent. It is obvious that this high nonresponse will not only decrease sample size and correspondingly increase variances of estimates from these data, but the results might also be biased if response is selective. There is a large literature on methods to compensate for nonresponse, covering everything from calibration methods including standard post-stratification, imputations, to more sophisticated model-based methods. The key to a successful compensation is to understand the causes of nonresponse. This is also important because of its relevance to survey design, where resources have to be allocated in line with the possibly conflicting goals of increasing the precision of estimates and reducing nonresponse biases.

There is an increasing literature on the causes of nonresponse, with more or less successful attempts to build models explaining response behavior. These attempts have been constrained by the usually very limited information available in the sampling frames. Researchers have then resorted to comparisons between the responding part of the sample and results from smaller but intensive studies of nonresponding sample members, using the assumption that those who could be converted tell us something about those who

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belong to the hard core of nonrespondents. They have also made comparisons with larger surveys with more reliable measures and population statistics. Only rarely has it been possible to match individual survey records to reliable register data for the same individuals. The situation is somewhat different in panel surveys, because in a panel one can use information given by the respondents in a previous wave of data collection to explain response behavior in a more recent wave (see for instance Brose and Klevmarken 1993; Lepkowski and Couper 2002; Nicoletti and Peracchi 2005). The results from these studies are interesting and important, but they do not necessarily carry over to a cross-sectional survey or the first wave of a panel survey.

It is well-known that response is usually much lower in the first wave of a panel survey than in successive waves and that attrition thus takes place in an already selected sample. People who are notoriously difficult to trace and convince have already been eliminated from the sample in the first wave[3] (see Laurie, Smith, and Scott 1999). Lepkowski and Couper (2002) argue that the response process in the first wave is fundamentally different from that of subsequent waves. This is both because of self-selection of the sample units and because of the extra information and organizational experience gained by the survey agencies at each successive wave. Fitzgerald, Gottschalk, and Moffit (1998) reported the same experience from the Panel Study of Income Dynamics (PSID). The attrition between the first and the second wave was 12 percent, whilst for the next 20 waves attrition was on average between 2.5 and 3.0 percent.

Another problem with using data from a previous survey wave to explain response behavior is that survey data always have measurement errors and other types of nonsampling errors. Depending on the variables used, this might become a problem when estimating a response model.

In this study we have the advantage of having exceptionally good sample frame data that can be used to explain response behavior. The sample frame was the 2001 wave of the longitudinal register-based data set LINDA of Statistics Sweden. LINDA is a random sample including a few hundred thousand individuals from the Swedish population. Register data include population censuses, schooling, income, wealth, tax data, etc. The sources of these register data are various administrative and statistical registers of Statistics Sweden such as the register of educational attainments, the income register, the wage rate register and registers from the Swedish social security system and labor market authority.

From LINDA we selected by simple random sampling a smaller sample of 1,430 individuals 50–84 years old to which CATI interviews were administered by Statistics Sweden.[4] These telephone interviews included sequences of questions taken from the U.S. Health and Retirement Study (HRS) survey and the European Survey of Health, Age, and Retirement in Europe (SHARE) and adapted to Swedish circumstances.[5,6] There were thus questions about health, labor force participation, wages, income, and wealth. Most of these

[3] Depending on design one might try to recruit those who did not participate in the first wave to participate in a second wave, but in many surveys this is never attempted.
[4] For this age group LINDA included 137,557 individuals and the population size was 3,026,499.
[5] The web address of HRS is http://hrsonline.isr.umich.edu/, and of SHARE www.share-project.org
[6] The 50–84 age cohorts were used because both the HRS and the SHARE surveys cover the population 50+. The restriction to people below the age of 85 was enforced to avoid the response problems that arise when respondents suffer from dementia or have other types of illnesses related to old age.

questions were about "facts," not about feelings, perceptions and attitudes. The average interviewing time was less than 30 minutes. The field work was done in the period April 3–May 11, 2003, with nonresponse follow-up June 2–22. In this period most Swedes completed their self-assessment for income taxation, so the information needed to answer questions about incomes, assets, and taxes should have been timely.

Prior to the field work the questionnaire was tested in the cognitive laboratory of Statistics Sweden and in a small pretest. Experienced telephone interviewers were used. They got a four-hour training session focusing specifically on our survey and they were afterwards asked to train on the questionnaire before being allowed to work in the field. The nonresponse follow-up was done by a few very experienced interviewers.

Thus the contribution of this article is an analysis of the response behavior in a cross-sectional survey with standard questions about health, income, taxes, and assets using unusually rich sampling frame data from the registers of Statistics Sweden and a model which simultaneously explains contact and cooperation.

2. Reasons for Nonresponse

2.1. A Literature Review

Singer (2006) gives a brief but interesting review of general trends in research about nonresponse in household surveys. Groves and Couper (1998) summarized and evaluated the literature on unit nonresponse in household cross-sectional surveys prior to the mid 1990s. They did this by separately analyzing contact and cooperation. Contactability is primarily a function of physical barriers to accessing the respondents, the households' at-home pattern, the interview mode and the contact schedule of the interviewers. The explanation of cooperation is more complex, involving the interaction of survey design, survey topics covered, the organization behind the survey and its perceived motives to carry out the survey, interviewer behavior, and demographic, socioeconomic, and psychological influences on the respondent.

The design properties are known, data about the respondents might be obtainable from the sampling frame, but it is more difficult to get detailed information about the interaction between interviewer and respondent. Process data from the field work sometimes give information about the number of contact attempts, reasons for noncontact/refusal, and perhaps also the interviewer's experience. In some surveys the interviewers are asked to summarize their experiences from each interview, but this is not common practice, and usually the important interaction between interviewer and respondent remains unknown.

In this article we report the results from a study of the outcome of one particular survey which was fielded by one survey organization using only one mode of data collection. Unfortunately, we have no data about the interviewers or their interaction with the respondents. We thus focus on the characteristics of the respondents and how they determine response. For the same reason the brief literature review to follow also has the same focus.

Groves and Couper (1998) found that contactability was lower in urban than in rural areas, a finding replicated in many other studies. It is not clear why this is so. One potential explanation is that there are many multi-family houses in urban areas with access limited

by entry barriers of various kinds. Another is that people spend less time at home in urban areas. Commuting takes time and there is a greater supply of out-of-home events. It is also possible that crime rates are higher in urban areas and that trust in other people is therefore weaker. One might thus be more reluctant to let an interviewer into one's home in urban areas. Still another potential explanation is that the proportion of singles and small families is higher in urban areas than in rural. Households with more adults and with children are easier to contact because the probability that someone will be at home is larger. Older adults also tend to be at home more frequently than young adults.

Groves and Couper (1998) note that previous studies have shown that cooperation rates are lower among lower socio-economic groups, among racial/ethnic minority groups, and among the elderly. However, they find that once contacted these groups, that tend to be poor, appear no different than other groups when they control for social environment as measured by urbanicity, population density, crime rate, and population proportion under 20 years old. One might however note that among these variables only population density emerges as significant in their own study and the only indicator of poverty is the house value, which is likely to pick up differences in the degree of urbanicity.[7]

Another conclusion from the Groves and Couper (1998) study is that young and old respondents have a higher cooperation rate than middle-aged ones. The authors speculate that there are different forces driving young and old. Young persons may have more experience of "standardized information seeking" from schools and jobs and be more curious about such efforts than older persons, while the latter may "maintain norms of civic duty regarding requests from government" and academia (p. 150). These results were obtained after controlling for if the household was a single-person household. It is well-known that it is more difficult to gain the cooperation of persons who live alone than of persons who live in multi-person households. Many old persons are singles, and according to Groves and Couper (1998) old age does not decrease the probability of cooperation once one has controlled for household size. The smaller cooperation rate of single-adult households is interpreted as a result of less social integration of these households. The authors also conclude that once socioeconomic status is controlled for (primarily measured by house value), the cooperation rates of minority groups are much closer to those of the majority group.

Socio-economic status is an elusive concept and can be operationalized in many different ways using information on, for instance, income, wealth, education and occupation. It thus comes as no surprise that the literature on nonresponse shows a diversity of results. We just note a result from a previous Swedish study, Lindström (1983), which found that respondents tended to have higher incomes and less social assistance benefits than nonrespondents.

In their literature review Särndal and Lundström (2005) concluded that the response rate is usually expected to be lower among metropolitan residents, single persons, members of childless households, older persons, divorced or widowed persons, persons with low educational attainment, and self-employed persons.

[7] The variables used are not clean measures of socio-economic status. It is a mixture of the monthly rent for renters and a self-estimate of the house value for house owners.

One conclusion that came out of the Groves and Couper (1998) study was that the probabilities of contact and cooperation had distinctly different explanations. Lynn et al. (2002) also made a distinction between the difficulty of contacting sample members and the difficulty of obtaining cooperation once contact is made. In a descriptive analysis based on various health and socio-economic surveys from the UK they found that the probability of participation was not dependent on the number of calls until contact. They also tested the hypothesis that households that were hard to contact have other characteristics than households that were easy to contact. Their main results were that respondents who were hard to contact were more likely to be smokers and drinkers, to have low blood pressure, and to be employed, and less likely to have a severe illness, to be younger, and to be White.

While many of the studies of nonresponse in cross-sectional surveys (first waves of panel surveys) are constrained by the usually limited information available about all sample members from the sampling frames or other sources, studies of attrition in panel surveys offer richer model specifications with more explanatory variables. (The smaller number of studies of cultural differences in nonresponse to cross-sectional surveys compared to the much larger number of studies of attrition in panel surveys in Tables 4.1 and 4.2 in Johnson et al. (2002) is suggestive.) For this reason it is of interest also to review some of the results from studies of attrition in panel surveys, even if these results do not necessarily immediately carry over to cross-sectional surveys.

Previous empirical research has suggested that attrition from a panel is more likely for individuals who are on welfare, unmarried, older, and non-White. Also, attritors have less education, work fewer hours, have lower labor income, and are more likely to rent their homes than the average respondent (Fitzgerald, Gottschalk, and Moffit 1998). Zabel (1998) concluded that attritors were more likely to live in urban areas, be non-White and unmarried, have fewer children, and rent their homes. Campanelli, Purdon, and Sturgis (1997) analyzed attrition both on a household level and on an individual level. Their main results are in line with the ones above, i.e., respondents who are less well-off are less likely to be included in the survey.

In decomposing attrition into noncontact and refusal Campanelli, Purdon, and Sturgis (1997) found, in line with previous research, that the two groups have different socio-economic characteristics. Non-Whites were harder to contact than Whites, as were unmarried respondents compared to married. It was hard to establish contact with young respondents, but once contacted they were generally cooperative. For elderly respondents it was the other way around. Households with no children were more likely to refuse, as were households with many working members, and households consisting of couples.

The sample of The American Time Use Survey (ATUS) was drawn from the eighth wave of the Current Population Survey (CPS) and nonresponse in its first wave can for this reason be seen as attrition rather than initial nonresponse. In their study of response behavior in the first wave of ATUS Abraham, Mailand, and Bianchi (2006) tested the hypothesis that "busy" people were difficult to contact and also less willing to cooperate. Their multivariate analysis gave some but not very much support to this hypothesis. People who worked long hours had a somewhat higher probability of noncontact, but there was no significant difference in probability of refusal once contacted. Married people with a working spouse were not more difficult to contact than others, and if the spouse worked long hours the

probability of cooperation was even higher than average. The presence of children had no significant effect on contact and cooperation for married sample members, but for unmarried ones, children aged 6–17 increased the probability of contact. Other results were very much in line with those of previous studies. Renters and sample members living in big cities had relatively high noncontact rates, while their cooperation did not differ from average. Households with low or zero incomes were both difficult to contact and unwilling to cooperate. The more schooling, the higher the contact and cooperation rates were.

Finally, Nicoletti and Peracchi (2005) modeled the response behavior using a bivariate probit model that distinguished between contact and cooperation. They used data from the European Community Household Panel (ECHP). Most of their results are in line with what is expected from previous research. They found that the number of children and home ownership increased the probability of contact, while the number of adults in the household and the equivalized household income (household income divided by the number of household members) were both insignificantly different from zero. They also found that being out of the labor market increased the probability of cooperation whereas being single decreased it. There was no significant effect of the age or education of the respondent.

2.2. *Our Survey*

In the remainder of this section we will discuss contact and cooperation difficulties arising in our survey. Statistics Sweden had mailing addresses for everyone – the addresses which the respondents had used when registering with the tax authorities – and through computerized telephone directories they could get the telephone numbers of most of the respondents. However, it is possible to be registered at one address and live somewhere else. For instance old people might keep their old home while they stay for a longer or shorter period in a nursing home. In this case they might not even have a private telephone. Many Swedes have secondary homes in the country and when they are retired they sometimes live there for longer or shorter periods, not only in the summer. Cell phones have become very common and should in principle increase the chances of reaching people, but the telephone directories have not always full coverage of all cell phone numbers. Some people opt in favor of only having a cell phone and no conventional phone, but this is not as common among older people. According to the surveys of the Swedish National Post and Telecom Agency 95 percent of the Swedish population aged 16–75 have a regular landline telephone and 3 percent have no telephone. About 90 percent have a cell phone.[8] In our survey contacting people meant getting the right telephone number and then getting them on the phone. As usual many attempts were made at varying times of the day and on different days of the week. At the end of the fieldwork period telephone numbers were still missing for 70 respondents and one respondent had an unlisted number. This is about what one could have expected given the telephone coverage in Sweden.

After contact has been established it is very much dependent on the interviewer whether it is successful or not. Unfortunately our survey data do not provide any information about the interviewers, so it is impossible to estimate any interviewer effects on response.

[8] *Svensk telemarknad*.

All interviewing was done from the Örebro branch of Statistics Sweden and interviewers called to all areas of the country. The area in which the respondent lives is thus not confounded with the interviewer. Because the CATI system allocated respondents to the interviewers without knowing the "track record" of the interviewer it is a plausible hypothesis that any interviewer effects are independent of the characteristics of the respondents. However, there is one exception: the more difficult cases needing nonresponse follow-up were turned over to the most skilled interviewers when the regular field-work period ended.

What is possible to do in our study is to model response as a function of the characteristics of the respondents. In explaining the probability of a contact we need variables that capture entry barriers, that some people are more mobile than others and that very old people are difficult to contact because of their age and because of illnesses such as dementia. Once contacted the decision about participating in an interview depends on the time-cost of the respondent and the presence of any competing activities. It also depends on the respondent's understanding of and interest in the issues to be brought up in the interview and the general purpose of the survey. There is also the concern about invasion of privacy. Even if people are interested in contributing to a health survey, many are reluctant to reveal information about wages, income and in particular wealth.

3. Explanatory Variables and Descriptive Analysis of Response Frequencies

At the end of May 2003 the response rate was 56.5 percent and the proportion of refusals was 19.6 percent. After the conversion attempts in June the total response rate increased to 61.6 percent and the proportion of not found was reduced by 2.9 percentage units and the proportion of refusals by 3.0 percentage units. In the end 22.6 percent of the sample members refused and 15.8 percent could not be found. The latter figure, however, includes 12 individuals who were classified as overcoverage and should have been eliminated. If this is done the response rate increases to 62.1 percent.[9]

Before proceeding to a multivariate analysis we start by motivating our choice of explanatory variables and analyzing a number of tables showing the association between response and the selected variables. With each table there is a chi-square statistic for a test of independence and the corresponding *P*-value. A significant test suggests that an association is stronger than one could expect from chance. These tables, however, only display bivariate relations, and any association or lack of association could well change in a multivariate analysis. For instance, as shown in Table 1 there is virtually no difference in the response behavior of males and females, but we still prefer to include this variable in our multivariate analysis, because gender might be confounded with other variables and while it is often available in sampling frames it is of interest to find out if there is any partial effect. We expect to find that females have a higher probability of contact than males, because they are less mobile and more frequently at home. Their probability of cooperation might, however, be lower. Even if the time-cost of working females usually is

[9] These individuals had either died or moved abroad between the day of selection and the day of the interview.

Table 1. Response rates by gender

Status	Male		Female		Total	
	N	%	*N*	%	*N*	%
Responded	412	61.2	469	62.0	881	61.6
Refusals	149	22.2	174	23.0	323	22.6
Not reached	112	16.6	114	15.0	226	15.8
Sample size	673	100.0	757	100.0	1,430	100.0

Chi-2(2) = 0.709 (0.702)

somewhat lower than that of males, because females have lower wages, females tend to be more sensitive to the issues of invasion of privacy and this effect might dominate.

Even though not all studies have found a clear relation between the age of the respondent and the frequency of contact and cooperation, we expect to find one. Young people are more mobile than older people and thus more difficult to contact. In our case the youngest cohorts are excluded from the study, but we expect to find that those who are at the peak of their careers are more difficult to contact than those who are retired. However, many retirees in their sixties and early seventies might also be mobile, going on vacation trips, spending time at their vacation houses, visiting children, etc. We might also find that some of the oldest old are relatively difficult to contact because of the increased prevalence of health problems in this age group, but as already mentioned our survey does not include people older than 84.

The relation between the probability of cooperation and age is more difficult to anticipate. Before retirement time-cost is at its peak for many respondents, and for this reason one might expect to find a larger probability of cooperation among the elderly. However, older respondents might be more sensitive to the issue of invasion of privacy than younger ones, they might also find it tiring to spend half an hour on the telephone and be more reluctant to bring out any documentation needed to give good answers.

The estimated age effects will also depend on other variables we choose to include. Some of them might pick up what otherwise would be interpreted as an age effect. It is difficult a priori to assume any particular functional form for the relation between response and age. For this reason we have chosen to work with age group effects, which will permit data to determine the shape of the relationship.

Table 2 shows that response rates are smallest among the youngest (50–55) and the oldest. But this result hides reversed age trends among refusals and not reached. Refusals increase with age while not reached seems to be a bigger problem among people below the age of 71.

Schooling is expected to influence response behavior directly as well as indirectly as an indicator of other variables. A higher education might increase the understanding of the research issues involved in our project and make the respondent more sympathetic towards research. Schooling is also an indicator of labor market career and pay, and thus of availability and time-cost. Also after retirement respondents with long schooling are expected to be relatively more mobile, if for no other reason because they tend to have higher incomes. We thus expect schooling to have a negative influence on contact, while there are countervailing factors determining cooperation. There is no reason to believe that the effects of schooling are linear or take any particular nonlinear functional form, so we

Table 2. Distribution of response status by age

Status	Age group							
	50–55	56–60	61–65	66–70	71–75	76–80	>80	All
Responded	211	198	133	108	97	90	44	881
	59.60	*63.46*	*65.84*	*61.71*	*62.18*	*59.60*	*55.00*	*61.6*
Refusal	77	48	46	39	42	45	26	323
	21.75	*15.38*	*22.77*	*22.29*	*26.92*	*29.80*	*32.50*	*22.6*
Not reached	66	66	23	28	17	16	10.0	226
	18.64	*21.15*	*11.39*	*16.00*	*10.90*	*10.60*	*12.50*	*15.8*
All	354	312	202	175	156	151	80	1,430

Chi-2(12) = 32.686 (0.001)
Note: Column percent in italics.

will work with three discrete dummy variables: Compulsory schooling, high school and university.

Register data on schooling are not ideal. They originate from census data, from examination registers for all levels of education, and from surveys concerning immigrants. The information on education obtained abroad is incomplete. The surveys concerning immigrants only provide part of the information. In all, data on schooling are missing for about 1.5 percent of the population covered. The major problem with these data, however, is that they only cover people in the age bracket 16–74. There are no register data for those who are 75 and above. In our sample we have missing data on the register schooling variable for 265 respondents. We have interview data for 150 of these. Most of them, 73 percent, fall into the group with lowest education. In our multivariate analysis we have chosen to use the survey information for the 150 respondents and code the remaining 115 as having missing schooling data. We believe that most of these 115 respondents have at most basic schooling. The proportion of immigrants is twice that of the whole sample, 8 percent compared to 4.

Table 3 shows that there is no strong association between schooling and response behavior. (The high Chi-2-value is generated by the missing schooling category.) The response rate is a little higher among respondents with university education, and respondents with only compulsory schooling are harder to convince than respondents with more schooling. None in the group with missing schooling data responded, most of them refused to participate. This result strengthens our belief that most of them are immigrants with limited knowledge of Swedish.

The variables household size and if married are expected to have a positive effect on the probability of contact, while any effect on cooperation is less obvious. Table 4 confirms this for marital status. Unmarried persons are less likely to respond than married. Most of this difference comes from a higher frequency of not reached for unmarried, while the difference in refusal rate is small.[10]

[10] The group unmarried includes people that are cohabiting but not legally married. A similar table but classified by "singles" and "couples", where the latter group includes married and cohabiting with common children, gave virtually the same result. In the age group 50 + most couples are married.

Table 3. Distribution of response status by education

Status	Compulsory schooling	High school and at most 2 years of university	More than 2 years of university	Missing value	All
Responded	339	355	187	0	881
	66.3	*66.5*	*69.3*	*0.0*	*61.6*
Refusal	98	95	47	83	323
	19.2	*17.8*	*17.4*	*72.2*	*22.6*
Not reached	74	84	36	32	226
	14.5	*15.7*	*13.3*	*27.8*	*15.8*
All	511	534	270	115	1,430

Chi-2(6) = 225.92 (0.000)

Note 1: Column percent in italics. Note 2: Register data on schooling are missing for respondents older than 75 years. Survey information was used for 150 respondents.

Table 5 gives similar information for household size. The bigger the household, the lower the frequency of not reached, while there is no major difference in refusal frequency.

The most frequently used time-cost measure is the hourly wage rate. This variable is unfortunately not included in our register data, but we have a measure of a monthly wage rate. Because many sample members are retired they do not have any wage rate. One approach to obtaining a time-cost measure for those who do not work is to estimate a wage rate for them had they worked. This can be achieved if a labor supply and an earnings function are estimated jointly with the contact (cooperation) function; for an application to panel data, see Brose and Klevmarken (1993). In our case it is probably not very meaningful to estimate such wage rates for people who retired quite a few years ago. Very few Swedes work after the age of 65. Instead we have chosen to use the wage rate measure only for those who have a wage. It is expected to have a negative effect on cooperation. If there is any contact effect it might also be negative. People with high wage rates tend to work long hours and might be difficult to reach. In addition we introduce a dummy variable that takes the value one if the respondent has no wage income. We expect that it will have a negative effect on contact, because those who have no job tend on average to be more mobile, while we have no prediction as to its effect on cooperation.

There is no clear association between the monthly wage rate and response behavior (see Table 6). The refusal rate increases a little with increasing wage rate, while there is no

Table 4. Distribution of response status by marital status

Status	Married	Unmarried	All
Responded	561	320	881
	66.63	*54.42*	*61.6*
Refusal	194	129	323
	23.04	*21.94*	*22.6*
Not reached	87	139	226
	10.33	*23.64*	*15.8*
All	842	588	1,430

Chi-2(2) = 47.349 (0.000)

Note: Column percent in italics.

Table 5. Distribution of response status by household size

Status	1	2	3 or more	All
Responded	284	430	167	881
	55.47	*64.76*	*65.75*	*61.6*
Refusal	113	154	56	323
	22.07	*19.65*	*22.05*	*22.6*
Not reached	115	80	31	226
	22.46	*14.45*	*12.20*	*15.8*
All	512	664	254	1,430

Chi-2(14) = 38.25 (0.000)
Note: Column percent in italics.

trend in the proportion of not reached. We thus find only a very weak indication of a time-cost effect on cooperation.

Table 7, however, suggests that having a paid job influences response behavior. Those who do not work are both more difficult to contact and more difficult to convince to cooperate. We note, though, that the employment indicator probably is confounded with age, schooling and other variables.

Previous results suggest that those who are relatively less well-off are more difficult both to contact and to get to cooperate. For this reason we have included in our analysis disposable income per capita and the indicators: if on welfare, if unemployed and if immigrant. Table 8 confirms the finding that respondents in low-income families have a much lower response rate. They are both harder to contact and harder to convince to give an interview. There are no large differences between people with average incomes and those who have high incomes.

Although there are few respondents that have received any welfare, Table 9 suggests that those who are on welfare are difficult to find and also difficult to recruit for an interview.

Whether a respondent had been unemployed in 2002 had no significant effect on response, while immigrants are both difficult to contact and to recruit for an interview (see Table 10).

Previous studies have also found that it is more difficult to contact respondents in urban areas than in rural. We thus include indicators of the degree of urbanization. Living in one of the three major metropolitan areas is the standard of comparison in our multivariate

Table 6. Distribution of response status by the monthly wage rate (SEK)

Status	$I \leq 10{,}000$	$10{,}000 < I \leq 20{,}000$	$I > 20{,}000$	All
Responded	155	167	202	524
	69.8	*69.9*	*65.6*	*68.1*
Refusal	33	42	61	136
	14.9	*17.6*	*19.8*	*17.7*
Not reached	34	30	45	109
	15.3	*12.6*	*14.6*	*14.2*
All	222	239	308	769

Chi-2(4) = 2.964 (0.564)
Note: Column percent in italics.

Table 7. Distribution of response status by employment

Status	If wage rate	No wage rate	All
Responded	524	357	881
	68.14	*54.01*	*61.6*
Refusal	136	187	323
	17.69	*28.29*	*22.6*
Not reached	109	117	226
	14.17	*17.70*	*15.8*
All	769	661	1,430

Chi-2(2) = 32.018 (0.000)
Note: Column percent in italics.

analysis below, while we have dummies for other urban areas and rural areas. We also use a dummy indicator if the respondent has a secondary home and expect that the probability of contact will be relatively smaller for this group.

Table 11 confirms that it is more difficult to reach people in urban areas than in rural, while interestingly the refusal rate is higher in the rural areas. The secondary home indicator does not give the expected result (not shown). There is no difference in contact rate between those who have and do not have a secondary home, while people with a secondary home more frequently cooperate.

We use three indicators of the health status of the respondent: if the respondent got any sickness benefits in the survey year,[11] if the respondent had stayed for at least one night in hospital during the year, and if the respondent had any psychiatric diagnosis in 1997–2002. None of these indicators necessarily show that the respondent is sick or in hospital at the time of the interview, but given that we know that the respondent has been sick, the probability of contact should be relatively high because the respondent is at home and – if not too ill – able to answer the phone. The probability of cooperation might however be low. Similarly, if the respondent has gone into hospital, the probability of contact is likely to be low. Respondents with a psychiatric diagnosis might have both a reduced contact probability and a reduced cooperation probability.

Looking at raw data we found no significant difference in contact and cooperation frequencies between those who had collected sickness benefits and those who had not. Respondents who had been in hospital in the survey year had a lower contact frequency, while there was almost no difference in cooperation frequency. The *P*-value of the Chi-2-test was only 0.06.

Register data from the Centre for Epidemiology at the National Board of Health and Welfare include historical information about past psychiatric diagnosis for the period 1984–2002. Using all this historical information would increase the proportion with a psychiatric diagnosis from 1.3 percent in 2002 to 8 percent. However it is not obvious that all years contribute useful information. Some of those who got a diagnosis in, for instance, 1984 might have recovered by 2002. For this reason we have only used data for a shorter period, 1997–2002.

[11] Sickness benefits are only paid to people who are not retired.

Table 8. Distribution of response status by disposable income (Y)

Status	$Y \leq 90{,}000$	$90{,}000 < Y \leq 120{,}000$	$120{,}000 < Y \leq 180{,}000$	$180{,}000 < Y$	All
Responded	136	181	305	259	881
	52.1	*52.5*	*69.9*	*66.8*	*61.6*
Refusal	72	99	74	78	323
	27.6	*28.7*	*17.0*	*20.1*	*22.6*
Not reached	53	65	57	51	226
	20.3	*18.8*	*13.1*	*13.1*	*15.8*
All	261	345	436	388	1,430

Chi-2(6) = 39.99 (0.000)
Note 1: Column percent in italics. Note 2: Disposable income in SEK per capita.

Table 9. Distribution of response status if on welfare or not

Status	No welfare	Welfare	All
Responded	875	6	881
	62.54	*19.35*	*61.6*
Refusal	312	11	323
	22.30	*35.48*	*22.6*
Not reached	212	14	226
	15.15	*45.16*	*15.8*
All	842	31	1,430

Chi-2(2) = 28.795 (0.000)
Note: Column percent in italics.

A total of 3.4 percent of the individuals on our sampling frame had a psychiatric diagnosis at least once in this period and many of these individuals had a psychiatric diagnosis for more than one year, and some of them also had other problems diagnosed.

In Table 12 below wee see the association between response and having at least one psychiatric diagnosis in 1997–2002. The response rate was 54 percent for this group. Eighteen percent could not be reached and 28 percent refused to participate. People with psychiatric problems are thus both more difficult to reach and more difficult to get to cooperate than average respondents.

Table 10. Distribution of response status by nationality

Status	Swedish	Non-Swedish	All
Responded	860	21	881
	62.82	*34.43*	*61.6*
Refusal	306	17	323
	22.35	*27.87*	*22.6*
Not reached	203	23	226
	14.83	*37.70*	*15.8*
All	1,369	61	1,430

Chi-2(2) = 27.766 (0.000)
Note: Column percent in italics.

Table 11. Distribution of response status by urbanization

Status	Major city	Other urban	Rural	All
Responded	282	474	125	881
	59.87	*62.04*	*64.10*	*61.6*
Refusal	94	182	47	323
	19.96	*23.82*	*24.10*	*22.6*
Not reached	95	108	23	226
	20.17	*14.14*	*11.80*	*15.8*
All	471	764	195	1,430

Chi-2(4) = 11.61 (0.020)
Note: Column percent in italics.

Table 12. Distribution of response status by having a psychiatric diagnosis 1997–2002

Status	No diagnosis	Diagnosis	All
Responded	862	19	881
	68.14	*54.01*	*61.6*
Refusal	313	10	323
	17.69	*28.29*	*22.6*
Not reached	206	20	226
	14.17	*17.70*	*15.8*
All	1,381	49	1,430

Chi-2(2) = 24.485 (0.000)
Note: Column percent in italics.

Just by looking at univariate distributions it is difficult to assess which variables are the most important ones to explain response, because many are confounded. We get, however, a very clear message from these tables, namely that response rates are much lower among low-skilled and low-income people, many of whom are found among the oldest in the sample. We also confirm findings from previous studies that the contact frequencies are higher in large households and among households living in rural areas.

4. A Sequential Bivariate Probit Model with Univariate Selection

The sequence of events we wish to model is first the contact and if contact is established the event of giving an interview. Following Nicoletti and Peracchi (2005) we will use a bivariate probit model. Let Y_1 be a dummy variable that takes the value 1 if a contact is established and Y_2 another dummy variable that takes the value 1 if an interview is obtained. Assume the following model

$$Y_1^* = \beta_1' X_1 + \varepsilon_1;$$

$$Y_2^* = \beta_2' X_2 + \varepsilon_2;$$

$$Y_1 = 1 \textit{ if } Y_1^* > 0; \textit{ otherwise } Y_1 = 0;$$

$$Y_2 = 1 \textit{ if } Y_1^* > 0 \textit{ and } Y_2^* > 0; \textit{ otherwise } Y_2 = 0;$$

where Y_1^* and Y_2^* are bivariate normal latent variables, while ε_1 and ε_2 are bivariate standard normal. The X-vectors are vectors of exogenous explanatory variables uncorrelated with the ε:s.

The parameters of the censored bivariate probit model have to satisfy certain constraints to make the model identifiable. If the covariates in the contact and participation equations are the same, then the model is not identified. Identification becomes possible if X_1 and X_2 are not identical, i.e., exclusion restrictions are needed. In this respect we were guided by previous results and common sense. For instance, the variables "if having a secondary home" and "if having been in hospital" were assumed to determine the probability of contact rather than the probability of cooperation. In the final specification a few insignificant variables were deleted from each equation. The model was estimated by maximum likelihood.

Table 13 gives summary descriptive statistics. Because the descriptive statistics suggested that the relation with age was not exactly the same for the contacts as for the response once contacted, two different age classifications were used, one in the contact equation and one in the response equation.

The maximum likelihood estimates are presented in Table 14. These results show that the probability of contact increases with age. Older people are more frequently at home to answer the telephone. There is no significant difference between males and females, while couples are easier to contact than singles. People with high school or university education are somewhat more difficult to contact than people with only compulsory schooling, but these estimates are uncertain. The group with missing schooling data has a small probability of contact. When this group was deleted from the analysis, the effect of the immigrant dummy became stronger. This suggests that there is a positive correlation between having no schooling data and being an immigrant. The missing schooling variable now picks up part of the immigrant effect.

The estimate of having sickness benefits is positive (sick people tend to be at home) but insignificant,[12] while having been in hospital reduces the probability of contact. We have also tried alternative specifications using the data on respondents having a psychiatric diagnosis. Replacing the hospital stay indicator with this variable in the contact equation also gave a negative and significant effect. If both variables were included both point estimates became negative but the *P*-values increased. The *P*-value of the hospital stay variable became 0.06 while the value of the psychiatric diagnosis variable increased to 0.16. For this reason we kept only the hospital stay variable as our preferred specification. The other parameter estimates were robust to these changes in the specification.

People who do not work for pay and immigrants are much more difficult to contact than the average person, and the probability of contact is smaller in the big cities than in other urban and rural areas. The point estimate suggests that those who are on welfare are more difficult to contact than average, but this effect is not well determined. There is no significant effect of being unemployed in addition to not working. The estimate for the wage rate variable was small and insignificant and thus dropped from the equation. Household disposable income had no significant effect either.

The point estimate for those who have a secondary home has the expected negative sign, but the standard error is relatively high.

There are a few variables which we have tried but then dropped from the model. One of them is the number of children in the household, which in previous studies has been shown

[12] Sickness benefits were insignificant in the cooperation equation and therefore dropped.

Table 13. Descriptive statistics of independent variables

Variable	Mean	S.D.
Age1 (≤55)	0.247	0.432
Age2 (56–75)	0.591	0.491
Age3 (76–)	0.162	0.368
Age4 (≤60)	0.466	0.499
Age5 (61–70)	0.263	0.440
Age6 (71–)	0.271	0.444
If female	0.530	0.499
If compulsory school	0.357	0.479
If high school	0.373	0.484
If university	0.189	0.380
If schooling missing	0.080	0.391
Wage (monthly)	9,490	12,870
If no wage	0.462	0.498
Disposable income	159,995	309,114
If sickness benefit	0.111	0.314
If social security	0.022	0.146
If major city	0.330	0.470
If urban area	0.534	0.498
If rural area	0.136	0.343
If secondary home	0.141	0.348
Household size	1.894	0.895
If unemployed	0.046	0.210
If married	0.588	0.492
If immigrant	0.042	0.202
If hospital stay	0.111	0.314

to explain response, in particular (many) children increase the probability of contact. In our case this variable was insignificant both in the contact and in the cooperation equations. This is perhaps not very strange, because in the age groups included in our study there are relatively few families with children and if they have children they are in the upper teens.

We have also experimented with a few interactions, namely gender x schooling, wage rate x schooling and disposable income x schooling, but they were all insignificant in both equations.

The probability of a successful interview increases with the age of the respondent. In particular those above 75 are willing to grant an interview. We do not find any gender effect in this case either. Household size and marital status are insignificant too.

Not having a job, being on welfare and being an immigrant all reduce the willingness to cooperate. The immigrant effect is however rather uncertain. Disposable income does not contribute to the explanation of cooperation in addition to these variables.

There is a significant time-cost effect as the effect of the wage rate variable is negatively significant. If we drop the income variable from the equation the wage rate effect moves closer to zero and becomes insignificant. In this case the wage rate variable thus picks up some of the positive effect of the income variable. According to a conventional economic time allocation model both variables should be included.

The schooling variable does not contribute much to the explanation of cooperation with the exception that respondents with missing data on this variable have a much lower

Table 14. ML estimates of a bivariate probit model

	Participation given contact		
Variable	Estimate	S.D.	*P*-value
Constant	0.839	0.298	(0.005)
Age2 (55–75)	0.209	0.118	(0.076)
Age3 (76–)	6.689	0.161	(0.000)
If female	0.009	0.092	(0.924)
If schooling missing	−13.991	0.248	(0.000)
If high school[a]	−0.194	0.136	(0.153)
If university[b]	0.026	0.125	(0.837)
Wage rate	−11.4e-06	5.72e-06	(0.045)
If no wage	−0.535	0.125	(0.000)
Disposable income	7.88e-07	6.87e-07	(0.251)
If welfare benefits	−0.815	0.374	(0.000)
Household size	−0.087	0.067	(0.193)
If married	0.165	0.145	(0.254)
If immigrant	−0.360	0.250	(0.150)
	Contact		
Constant	0.428	0.206	(0.038)
Age5 (61–70)	0.494	0.123	(0.000)
Age6 (71–)	1.154	0.183	(0.000)
If female	0.078	0.087	(0.366)
If schooling missing	−0.996	0.202	(0.000)
If high school[a]	−0.168	0.131	(0.201)
If university[b]	−0.044	0.124	(0.727)
If no wage	−0.316	0.131	(0.015)
Disposable income	1.66e-07	3.32e-07	(0.616)
If sickness benefits	0.152	0.151	(0.314)
If welfare benefits	−0.366	0.255	(0.152)
If urban area	0.208	0.093	(0.025)
If rural area	0.334	0.143	(0.019)
If secondary home	−0.184	0.132	(0.161)
Household size	0.065	0.067	(0.332)
If unemployed	0.110	0.207	(0.595)
If married	0.438	0.119	(0.000)
If immigrant	−0.403	0.189	(0.033)
If hospital stay	−0.252	0.133	(0.057)
Residual correlation	0.233	0.423	(0.596)
Log pseudolikelihood	−1,080.595		

[a]Includes individuals with a high school diploma or individuals who studied at the university for less than two years. [b]Includes individuals with more than two years at university.

probability of cooperation than everyone else. As already suggested, this result might mask effects that are unrelated to schooling.

In previous model runs the variables capturing the degree of urbanization became insignificant in the participation equation, and for this reason we dropped these variables.

Our model allows for a correlation between the contact and participation equation whereas Lepkowski and Couper (2002) assumed independence. They thus assumed that omitted variables have no joint effect on contact and participation. A more general assumption is that unobservables may influence both the probability of contact and that of

participation and thus create a correlation between the contact and participation equations. Results are not conclusive. The correlation is moderately positive but insignificant.

5. Concluding Remarks

From an economist's perspective it might be reasonable to believe that time-cost has a strong influence on the probability of contact and participation, and consequently that high wage earners and high income people are difficult to convince to participate in surveys. Confirming previous results about nonresponse in cross-sectional surveys and attrition in panel studies, this study shows that this notion is largely false. It is true that we have found a significant time-cost effect on participation but the major finding is that nonresponse primarily comes from the left tail of the income distribution. Respondents without work, on welfare, and immigrants are those who are difficult both to contact and to convince to participate. People at the peak of their careers are also difficult to contact and to convince to participate. As has been found in many other studies we have found that the probability of contact is relatively low in the big cities and among singles, but we could not find any significant decrease in cooperation.

This result would seem to have implications both for survey design and post-survey adjustment measures. The characteristics of the individuals that contribute to nonresponse suggest that this is a group which is rather uninterested in the research purpose of our survey and that measures should be taken to try to generate a greater interest. The characteristics of those who do not respond also suggest that this is a group in an economic situation such that they should be sensitive to economic incentives even if the latter are rather small.

In addition to focusing on the major group of the nonrespondents, contact efforts should focus on people who live in urban areas, who are single, have more than basic training, are at the peak of their work careers and have a secondary home.

Recent nonresponse research has focused on the circumstances under which nonresponse damages inference to the target population and results in biased estimates of population entities (Singer 2006). Groves (2006) demonstrated that high nonresponse does not necessarily result in biased estimates. In addition to the response ratio the magnitude of the bias depends on the correlation between the propensity to respond and the attributes the survey researcher is measuring. If there is no or only a very weak correlation there is no or only a small bias even if the survey is burdened by nonresponse. This implies that researchers who in their analysis focus on variables that explain the contact and cooperation probabilities or on measures that are highly correlated with these variables will suffer from a biased inference unless proper adjustment measures are taken. Our literature review and our own results are suggestive as to the nature of these variables. It also follows that calibration methods, which are designed to compensate for nonresponse should use variables and population information that explain response. According to our findings gender is *not* such a variable while, for instance, age, marital status, labor force participation, if immigrant, health status, family income and population density of the area are such variables.[13]

[13] Using the same data as in this study Johansson (2007), Chapter 4, compares the calibration approach applied to an earnings function to a model-based approach.

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