Effects of response burden in a continuous survey

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Abstract

By using a panel for collecting continuous data, an extra kind of measurement error is introduced: panel effects. If such a panel is frequently measuring, these panel effects tend to have a negative influence on the level of reporting: due to the burden, the respondents become less motivated, leading to underreporting, wave non-response and attrition. Since panel effects occur selectively across the population, neglecting these panel effects leads to serious problems. This paper describes some aspects of these processes in a consumer panel for expenditure data. An adjusted version of the model used by Meurs et al. for underreporting of trips in a trip diary is used to estimate the effects of the burden the registrations. It has been found that the burden leads to underreporting, zero-reporting and wave non-response. However, the results also suggest that loyalty towards the research organisation plays an important role.

1 Introduction

Several fields of research require a continuous stream of data, for instance if one is interested in behaviour that changes through time, or events that occur with a certain time-pattern. One way of collecting such data is by using a panel design: after regular periods the same respondents are asked particular questions. For example, every week households are asked how much they spend on a particular commodity. They can answer these questions in several ways: by telephone, by sending in an interview form, transmitting their questionnaire by computer, or by using a scanner to report items. The advantages of a panel design are that behaviour which changes over time can be analysed on an individual level and that respondents learn by repeatedly answering. One of the most important disadvantages is the high burden that the continuous questioning places on respondents. Especially in behavioural research, where questions are asked about how much money or time is spent on some good or activity over each period, the motivation of respondents tends to decrease, leading to underreporting, to wave non-response and finally to attrition (drop-out). When using a panel design, one has to consider these so-called panel-effects.

Reports on these problems are scarce. Most panels are commercial and do not provide such information. Among the few exceptions are the following.

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Van de Pol (1989) reports that attrition and panel-effects can be selective, i.e. that the group of drop-outs is not random, but depends on certain characteristics of the respondents. The degree of attrition and other panel-effects also depends on the kind of questions: if the questions are complex, respondents become experienced with time with the result that panel-effects will be positive. When the questions are monotone (as in behaviour research) respondents become demotivated and the panel-effects negative.

Olivier (1987) analyses coverage-factors. A coverage-factor of a panel describes how well a panel is able to present estimates for certain statistics in the population. When expenditure is analysed, the coverage-factor can be found by comparing the expenditure registrations of the panel with ex-factory reportings. A coverage-factor of one means that the panel describes the population perfectly. In practice, a coverage-factor of one is an exception. Olivier finds coverage-factor estimates that are lower for expensive products (0.68), and higher for cheaper products (1.34) when a consumer panel is used. In this way, the market-shares for these products will be biased. It is often said that the levels of the interest variable might be wrong, but that at least the trend is correct. However, Olivier shows for one product that the market-share of the product on some market, according to the consumer panel, decreases over 12 years, while the 'real' market-share increases over that same period.

Silberstein and Scott (1991) have studied underreporting using expenditure diary surveys. In two consecutive weeks a diary had to be filled out by the respondents. Silberstein and Scott found both intra-week and inter-week variation: reporting levels decrease per week and per day. This effect, which Silberstein and Scott call the 'fatigue or reduced interest effect', is different for different kinds of products. The per day decrease is highest in the first days of the first week.

Meurs et al. (1989)/*BGC* (1988) analysed these effects in a mobility-panel. They also found a decrease in the number of trips made, or underreporting of trips, a decrease which is highest in the first days of the first wave. They split the underreporting into two effects: a 'within-wave' and a 'between-wave' effect. Because the within-wave effects become smaller with subsequent waves, there is also an interaction between the within-wave and between-wave effects. These were put in a regression with pooled data (i.e. all observations of all respondents were considered as separate observations). In this way, Meurs et al. were able to estimate the within-wave and between-wave effects on several mobility variables: ordinary trips are more underreported than rare trips, and longer trips are less underreported than shorter ones. Respondents who have participated longer tend to report higher mobility. All these effects together result in considerable underreporting in mobility.

Ridder (1992) analysed the same data to describe the effect of attrition. He states that households that make more trips are more likely to drop out. When regressing the total number of trips on several background characteristics of the households and dummy variables for the waves, the decrease in registrations is not explained by observed differences between households that leave and households that stay. This leaves two possibilities: either there is a downward trend in mobility, or there are differences in unobserved characteristics of the respondents in the panel. This leads him to investigating response behaviour.

Overlooking these findings, we suggest that the high burden of registrations on the respondents can lead to the following sequence of reactions:

Firstly respondents start to report less than they should, e.g. because they become less precise in filling in their diaries. This is what we call underreporting;

Secondly respondents start to respond zeros while they had some purchases, to save the time of giving all requested items. This is an extreme case of underreporting;

Thirdly respondents start to respond less regularly, so that some weeks they do not respond at all, while other weeks they do co-operate. This is known as wave non-response;

Finally respondents drop out (attrition).

We should note here that these reactions do not automatically lead to a decrease in registrations at the aggregate level: if they occur randomly in the sample, no problem arises. On the other hand, if the respondents who drop out are those that reported at a low level before leaving, and if they are replaced by enthusiastic new panel-members, this will actually lead to an increase in registrations. Extra conditions are therefore needed if these reactions are not to lead to a decrease in registrations.

In this paper, we shall look at the possibility of isolating the different individual reactions in a consumer-panel that reports expenditure on a weekly basis. We will first give an idea of the seriousness of the problems described here for a specific case and then estimate the effect of the burden on the possible reactions. We use the same model for the different reactions but with a different dependent variable. For underreporting, the dependent variable is reported expenditure (reportings with only zeroes excluded); for zero-reportings, the dependent variable is the number of zero-registrations and for wave non-response the dependent variable is the number of missing observations. These dependent variables are regressed on household-characteristics, like family-size, age, income, education-level and taste and the burden of reporting on the household.

Because the panel concerns behaviour, we expect a negative panel-effect (i.e. the effect of the burden). In our design, the *total burden* (B) consists of the number of weeks a respondent was requested to participate up to time t, multiplied by the weekly burden of responding, here the number of items that has to be entered. Because this number of items to be entered is also affected by underreporting, we will approximate this number by the number of items that was entered in the first month. We realise that this variable is subject to measurement error, but to keep our analysis simple, this approximation will suffice.

On the other hand, respondents who have been members of the panel for a longer time may be considered *more loyal* towards the panel and, because they do their job better, to provide higher registrations than households that have only recently started; also higher than households that have dropped out early. Therefore, the total number of weeks (N) a household has reported will also be included in the analysis to signify loyalty.

Of course, *taste* also plays a role in the amount of the relevant commodity purchased, influencing the volume purchased in the first registration week. We assume this influence to be on a logarithmic scale, due to decreasing returns: if a person prefers a certain volume, he or she will prefer the double of this amount less than twice as much. Therefore, we will include the logarithm of the volume purchased in the first registration week (V_0) in our model (the subscript 0 instead of 1 avoids confusion with reported volume, subscripted with 1, 2,..., 6).

Besides the above mentioned factors we expect effects of household characteristics (H) on the reporting and of course variation over time (W). The reporting of this last fluctuation is often the real reason for the study.

We use the logarithm of the burden in our model, for we assume that the *increase of the effect* of the burden becomes smaller. For the same reason, we also assume the effect of the total number of reporting-weeks to be logarithmic. The model is then as follows:

$$y_{it} = \alpha + \Sigma_j\beta_j H_{ij} + \gamma\log(V_{0i}) + \Sigma_w\kappa_w W_w + \lambda\log(B_{it-1}) + \mu\log(N_i) + \varepsilon_{it} \tag{1}$$

where y_{it} is the registration for household i, $i = 1,...,n$, in week t, $t = 1,...,T$; H_{ij} is the j^{th} household-characteristic of household i; W_w is a dummy, that is equal to 1 if the observation refers to week w, and equal to 0 otherwise; B_{it-1} is the burden that a household i was exposed to until week t-1 (for the first week, there is no burden of previous registrations); V_{0i} is the total volume reported by household i in the first week it participated; N_i is the total number of weeks that household i had to report in the whole period.

With certain adaptations specific to our design, the model described above is the model used by *Meurs et al.* (1989). We can foresee two problems with this model.

The first problem is that pooled data are used. When pooled data is used, the assumption is made that all disturbance terms ε_{it} are identically and independently distributed. Dependence between the observations of one household is not taken into account. This will lead to unbiased and consistent but inefficient parameter estimates, and estimates of standard errors will generally be biased, leading to unreliable test results (for example see *Greene*, 1993).

The second problem is that we do not know whether our model specification is complete. It is assumed that for unbiased estimation of linear regression models the random error is uncorrelated with the exogenous variables. However, incomplete specification of the model results in biased estimates of the disturbance variance (for example see *Johnston*, 1984). The heterogeneity that results from this incomplete specification must therefore be taken into account. The panel design makes this possible. An alternative therefore is to use an explicit panel-model for T periods with person specific unobserved heterogeneity as an extra factor.

$$\begin{aligned} y_{i1} &= \alpha_1 + \eta_i + \Sigma_j\beta_j H_{ij} + \gamma\log(V_{0i}) + \mu\log(N_i) + \varepsilon_{i1} \\ y_{i2} &= \alpha_2 + \eta_i + \Sigma_j\beta_j H_{ij} + \gamma\log(V_{0i}) + \lambda\log(B_{i1}) + \mu\log(N_i) + \varepsilon_{i2} \\ &\vdots \qquad\qquad \vdots \\ y_{iT} &= \alpha_T + \eta_i + \Sigma_j\beta_j H_{ij} + \gamma\log(V_{0i}) + \lambda\log(B_{iT-1}) + \mu\log(N_i) + \varepsilon_{iT} \end{aligned} \tag{2}$$

where η_i represents the unobserved heterogeneity and W_w is represented by the constant a in each equation. If the heterogeneity is specified as a *fixed effect*, this will result in n extra parameters, while n will be large in typical panel designs. If we treat η_i as a *random effect*, a heuristic approach for estimating the model has been suggested by *Greene* (1993) which is said to lead to inconsistent estimates. Model (2) can also be seen as a special case of the Structural Equations Model. For such models, standard consistent estimators are available (*Bollen*, 1989). For more on heterogeneity in Structural Equations Models, we refer to *Muthén* (1994) and *Muthén and Satorra* (1995). Below we will use this approach to estimate the parameters of model (2), but before doing so we will first introduce the data used and show how these data are affected by the response burden of the respondents.

2 Research Design

The data-set with which we want to study the same kind of problems is a consumer-panel using a special form of computer-assisted self-administered questionnaire called Telepanel (*Saris and De Pijper*, 1986). All members of the panel are provided with a computer and a modem to receive the questionnaires, to return the answers and to co-operate in research in the absence of an interviewer. The questionnaire we used concerned expenditure on meat, poultry and eggs. The respondents kept a diary of their daily expenses on these products: for each item bought they note the volume, the price, the kind of package, etc. and at the end of the week they use this diary to answer the questionnaire sent to them by modem.

The panel used for this study has been organised by the Telepanel Foundation (STP) of the University of Amsterdam. The sample frame in this study was the telephone book, from which we intended to draw 3500 households. Because of the expectation that only 60% of the telephone-numbers refer to households, 5833 numbers were needed [(100/60) × 3500] to obtain these 3500 households. These households were drawn by a systematic procedure where a minimal cluster size of 5 per town was required. These original households were substituted by households with the same telephone number except for the last two digits (a so-called 100-bank). These last two digits were randomly chosen in order to include households with a secret telephone number (12%) in the sample. The sample was increased by drawing more than one person randomly from the 100-banks because a 60% co-operation rate was expected in the telephone interview and an 80% co-operation rate with the panel. Therefore 5833 × (100/60) × (100/80) = 12153 households were drawn. For more details of the sample design we refer to *Geldrop* (1993).

In the first round, 7971 numbers were called, and the people asked to co-operate in a short telephone interview for screening purposes. Of all numbers 11.3% were not reached after more than 15 calls at different times and 20.4% were not households, which means that 68% of the numbers led to a contact with a household. Of these contacts 61.2% were willing to co-operate in the telephone interview. At the end of this telephone interview, the people were asked to co-operate in the panel. Of these people 36.7% immediately refused to co-operate in the panel. Of the other households another 14% refused in a later stage. In the end 1419 households were found willing to co-operate in the panel. Because of differences between population-characteristics and sample-characteristics, only a limited group was asked for the panel and a second round was begun in order to select more households. The process for the next groups was the same. This process was continued till 2000 households participated.

In order to evaluate the quality of the sample an experiment was conducted over six months. These results showed that only a small number (9%) of the sample refused to co-operate because of the use of the computer (*Saris and De Pijper*, 1986). This number only decreased during the last years, due to the wider acceptance of computers in the society.

There was, of course, also attrition. Each year approximately 18% of the sample dropped out and had to be replaced. The substitution was a continuous process where households which dropped out were replaced by households drawn from a pool of households which were willing to participate, while the probability of drawing a household was adjusted due to the size of the gap between the population characteristics and the sample characteristics. Using this approach meant that the sample was self weighing. For details see *Geldrop* (1993).

3 Results

3.1 Descriptions

In our data, as in other reported studies, the decrease in registrations is clearly evident. This is shown in Table 1. The first part of the table shows a large decrease in reported expenses with time. This decrease in registrations is accompanied by an increase in zero-reportings and wave non-response. We should mention that the panel is renewed continuously. Since the new respondents are more motivated, we may expect their response behaviour to be better, which might explain the stabilisation seen after the second month. Altogether, the effect on registrations is so large and the observed process is so unlikely, that one cannot use such data without correction for the effects studied here.

The second part of the table shows that these effects not only occur for the aggregate data over all products but also for each product separately, and in fact for each product in a slightly different way.

Table 1: *Registrations and wave non-response.*

		Month					
		1	2	3	4	5	6
total	expense	100.0	98.0	90.2	91.1	87.8	84.5
	volume (excluding eggs)	100.0	93.8	87.0	87.0	80.8	82.2
	number of products	100.0	99.8	93.3	91.3	86.7	84.8
registration of zeroes		100.0	130.8	134.0	128.1	125.8	129.9
wave non-response		100.0	97.1	105.7	110.2	117.8	120.5
The total can be separated into the following four product groups							
red meat	expense	100.0	99.3	91.0	93.8	89.7	88.9
	volume	100.0	95.4	87.4	90.8	82.8	85.1
	number of products	100.0	99.4	92.9	92.9	89.6	90.3
meat products	expense	100.0	101.0	92.8	91.0	90.6	82.3
	volume	100.0	103.0	90.9	84.8	84.8	78.8
	number of products	100.0	102.1	95.9	92.8	87.2	84.1
poultry	expense	100.0	87.5	82.1	80.2	79.0	75.5
	volume	100.0	80.8	76.9	73.1	79.2	76.9
	number of products	100.0	90.9	87.9	81.8	81.8	75.8
eggs	expense	100.0	91.8	86.6	90.7	73.2	70.1
	volume	100.0	91.3	85.4	92.1	75.7	75.7
	number of products	100.0	91.3	85.4	92.1	75.7	75.7

The columns represent the sample means of the average weekly registrations for expenses, volumes and number of products as well as the number of reported zeroes and wave non-response per month; total volume is excluding eggs; month 1 ≡ 100.

Table 2: *Size of the panel.*

Reported in week	Started in week: 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	Tot.
1	849																								849
2	579	141																							720
3	650	87	119																						856
4	649	97	80	61																					887
5	624	87	70	34	25																				840
6	596	85	74	43	14	62																			874
7	628	94	61	40	17	43	68																		951
8	621	83	70	42	15	36	41	84																	992
9	574	77	59	35	15	31	40	55	44																930
10	574	79	54	36	16	33	46	55	28	54															975
11	581	82	70	35	15	34	40	46	30	38	37														1008
12	512	77	53	30	12	26	38	34	17	30	17	8													854
13	513	65	46	28	11	26	40	40	18	22	19	5	20												853
14	499	68	48	30	7	25	33	42	28	23	19	4	11	22											859
15	514	74	48	29	10	27	39	42	27	21	13	5	10	14	14										887
16	493	69	40	23	10	21	31	42	21	21	16	4	10	8	8	16									833
17	477	63	43	27	7	26	34	41	23	25	13	3	9	14	4	9	11								829
18	454	61	48	25	8	23	35	38	23	19	12	4	9	11	7	6	3	12							798
19	411	52	38	18	9	20	29	33	15	17	9	3	8	11	5	5	5	6	3						697
20	430	54	45	22	7	28	31	37	16	21	10	3	9	11	4	4	7	7	1	16					763
21	443	61	39	13	7	20	27	34	20	18	13	2	8	13	4	6	5	7	1	12	5				758
22	424	58	43	19	7	19	32	29	19	25	13	3	9	9	9	9	3	3	0	9	2	5			749
23	438	56	38	13	9	19	31	33	19	18	12	2	9	9	5	7	4	3	2	9	4	1	16		757
24	425	55	33	17	4	17	32	37	15	18	11	1	11	10	7	8	4	5	1	8	2	1	7	6	735
	849	141	119	61	25	62	68	84	44	54	37	8	20	22	14	16	11	12	3	16	5	5	16	6	

Each row displays the number of respondents who co-operated in each week of the panel, subdivided according to the week each became member of the panel.

Table 2 shows the number of respondents that participated each week. These numbers are subdivided by the week the household began reporting. In each column the attrition is clearly visible: for example, in the group beginning in the first week, only 50% of the households is still reporting in the 24th week. Of course this will have its effect on the registrations.

In what follows we will mainly concentrate on the effects displayed in Table 1. For these three effects we can use the same model, while for the process of attrition a different model is needed. We realise that neglecting the effects of attrition will not give a complete insight into the effects of response burden. However, inclusion of attrition in our model complicates matters too much.

3.2 Estimation of the effect of the burden

Firstly, we will analyse the effect of the burden of registration on the reporting-level of expenditure. For our analysis we use model (2). The dependent variable is the reported *total volume*, in kilograms. Eggs are omitted, since the quantity of eggs is measured by number. We will use the average week-volume in a month instead of weekly volume. In this analysis the extreme case of underreporting, the reporting of zeroes, was excluded from the analysis, and will be treated separately. Of course, not all zero-reportings are a form of underreporting. Some represent non-purchasing. On the other hand, households can decide not to respond both when no purchase is made and when they are either unable or unwilling to report. In the former case, we must replace the missing observation –resulting from non-response– by a zero, in the latter case, the observation remains missing. We know when a household was able or unable to report, but we cannot distinguish between the case where a household was unwilling to report, and the case where a household spent nothing. In some cases, however, we might recognise an expenditure-pattern for households that shop, say, once in two weeks. The Appendix shows, that such a pattern is so infrequent for these products in our data that we have not taken this factor into account.

The model is estimated with LISREL (*Jöreskog and Sörbom*, 1989), which is a standard package used for the estimation of Linear Structural Equation Models. The Maximum Likelihood criterion was used for estimation, which under normality provides consistent, asymptotically efficient parameter estimates. An expression for the asymptotic covariances is also present, as well as a goodness-of-fit statistic which is χ^2 distributed with known degrees of freedom. Although we might expect our exogenous variables to be non-normal, we used this estimator because the conditions for asymptotic robustness, as described by *Satorra and Bentler* (1990) and *Satorra* (1992), apply here, which means that consistent, asymptotically optimal parameter estimates will be obtained. Furthermore, the expression for the asymptotic covariances is still applicable except for the asymptotic covariances of the variances of non-normally distributed variables, and the goodness-of-fit statistic still is χ^2 distributed.

The results of these estimations are presented below for the underreporting, the number of zeroes and the non-response as dependent variable using model (2) for estimation. In order to compare the size of the effects the (completely) standardised coefficients have been presented while the significance of an effect is indicated by an asterisk *.

3.2.1 Underreporting

The first reaction shown by respondents to the burden of registration, is underreporting. As explained above, we will analyse this reaction using model (2), where the dependent variable is total volume, excluding zeroes. The estimation results for this model are summarised in Table 3.

It can be seen that the reported volume is affected not only by the size of the family, education-level and by taste measured by the volume in the first week as one can expect, but also by the burden on reportings. The effect of the burden indeed is negative. This means that households do underreport if the burden gets higher. We also see that the effect of total requested weeks, thus loyalty towards the panel, is significantly different of zero, and the effect of the unobserved heterogeneity on reported volume is considerable. Estimating the model without unobserved heterogeneity will not change the estimates much, but the squared multiple correlations decrease up to .24, with an average of .15. Moreover, the χ^2_{78} has a value of 436.51, with a probability of 0.00.

Table 3: *Reported volume*

effect of:	Month 1	2	3	4	5	6
log burden	—	−.21*	−.21*	−.21*	−.17*	−.20*
log total requested weeks	.13*	.19*	.19*	.19*	.16*	.18*
log first volume	.29*	.44*	.45*	.44*	.37*	.43*
family size	.17*	.26*	.27*	.26*	.22*	.26*
income[a]	.02	.03	.03	.03	.02	.03
age	.02	.03	.03	.03	.02	.03
education-level[b]	−.05*	−.07*	−.07*	−.07*	−.06*	−.07*
work of head of household	.00	.00	.00	.00	.00	.00
panel membership[c]	.00	.00	.00	.00	.00	.00
unobserved heterogeneity	.33*	.49*	.50*	.50*	.41*	.48*
squared multiple correlations	.35	.59	.62	.59	.41	.57
goodness-of-fit χ^2_{72}	91.54	(p=0.06)				

Completely standardised LISREL estimates of the model for total volume without zero reportings.

* significant at 5% level
[a] income measured on a 5-point scale
[b] education-level measured on a 4-point scale
[c] panel membership measured on a 3-point scale

The estimates above can be used to correct average reported volume for the effect of response burden. For this the parameter estimates for α_t, β_j, γ, λ and μ are entered in equation (2), together with the means of H_j, $\log(V_0)$, $\log(B_t)$ and $\log(N)$. Using these values, the sample means for reported volume will be reproduced. In table 4 the unstandardised parameter estimates for reported volume and the sample means for the exogenous variables are presented. In table 5 the predicted (= average) reported volume is shown. Corrected volume is computed by assuming the average burden equal to 0.

Table 4: *Parameter estimates and sample means*

t	1	2	3	4	5	6
α_t	2.07806	1.83544	1.72270	1.73707	1.73212	1.71748
	famsize	*income*	*age*	*education*	*work*	*membership*
β	.24879	.02312	.00201	−.07946	.01098	.00550
mean	2.33450	3.30823	49.92640	2.30648	.59194	2.59194
	log*taste*	log*burden*	log*loyalty*			
γ, λ, μ	.99673	−.36316	.33086			
mean	1.02807	↓	4.72979			
*log*burden$_t$	2.98343	3.65779	4.05940	4.33997	4.55576	

Table 5: *Predicted and corrected volume*

t	1	2	3	4	5	6
Predicted	1.88891	1.74491	1.65491	1.70591	1.68791	1.64690
Corrected	1.88891	1.87779	1.82825	1.91361	1.91529	1.89569

After correction for response burden, there is no longer a steady decrease in volume, giving a more realistic picture of consumption.

3.2.2 Zero reportings

The next reaction of the respondents is the reporting of zeroes. The maximum number of zeroes a household can report is sixteen, four for each of the four different product groups: *red meat, meat products, poultry* and *eggs* in four weeks. Apart from this change in the dependent variable, the rest of the model remains unchanged. The results of the estimation of the parameters for this dependent variable are given in Table 6.

Table 6: *Zero reportings*

	Month					
effect of:	1	2	3	4	5	6
log burden	—	.06*	.06*	.05*	.06*	.05*
log total requested weeks	−.48*	−.51*	−.51*	−.48*	−.50*	−.48*
log first volume	.07	.07	.07	.07	.07	.07
family size	−.13*	−.14*	−.14*	−.13*	−.14*	−.13*
income[a]	−.02	−.02	−.02	−.02	−.02	−.02
age	−.16*	−.18*	−.18*	−.17*	−.17*	−.17*
education-level[b]	.02	.02	.02	.02	.02	.02
work of head of household	−.08*	−.08*	−.08*	−.08*	−.08*	−.08*
panel membership[c]	.04	.05	.05	.04	.04	.04
unobserved heterogeneity	.58*	.62*	.62*	.58*	.60*	.59*
squared multiple correlations	.60	.63	.64	.55	.59	.56
goodness-of-fit χ^2_{72}	107.30	(p=0.0044)				

Completely standardised LISREL estimates of the model for the number of zero-reporting.

* significant at 5% level
[a] income measured on a 5-point scale
[b] education-level measured on a 4-point scale
[c] panel membership measured on a 3-point scale

In this case too the expected effects of taste, family size, age can be seen and the reporting of zeroes is only slightly caused by the high burden imposed on respondents. We see, however, that the more loyal the respondent is towards the panel, the fewer zero reportings are made. Again, unobserved heterogeneity has a large effect, in fact the largest effect: neglecting unobserved heterogeneity in estimation leads to a decrease in squared multiple correlations with on average .35, and an increase in χ^2 of 732.

3.2.3 Wave non-response

Although we found that we could treat missing values due to wave non-response and zero reportings similarly (see Appendix), in Table 7 we now show only estimates of the effect of the burden on the number of missing values. Observations with the maximum of four zeroes per week are not considered here.

Table 7: *Wave non-response*

effect of:	Month 1	2	3	4	5	6
log burden	—	.17	.16*	.13*	.12*	.11*
log total requested weeks	−.53*	−.55*	−.58*	−.54*	−.50*	−.49*
log first volume	.15*	.15*	.16*	.15*	.14*	.14*
family size	.05*	.06*	.06*	.06*	.05*	.05*
income[a]	.06*	.06*	.06*	.06*	.05*	.05*
age	−.09*	−.10*	−.10*	−.10*	−.09*	−.09*
education-level[b]	−.01	−.01	−.01	−.01	−.01	−.01
work of head of household	−.06*	−.06*	−.06*	−.06*	−.05*	−.05*
panel membership[c]	−.11*	−.11*	−.11*	−.11*	−.11*	−.11*
unobserved heterogeneity	.29*	.30*	.32*	.30*	.27*	.27*
squared multiple correlations	.33	.23	.27	.24	.21	.21
goodness-of-fit χ^2_{72}	1825.00	(p=0.0)				

Completely standardised LISREL *estimates of the model for wave non-response.*

* significant at 5% level
[a] income measured on a 5-point scale
[b] education-level measured on a 4-point scale
[c] panel membership measured on a 3-point scale

In this case the burden has a significant effect on the wave non-response but loyalty again has a large effect which serves to reduce the non-response. Other factors also have a minor but significant effect such as age and the amount of time respondents have already participated in the panel. Heterogeneity also has again a strong effect, and if omitted in estimation squared multiple correlations decrease on average with .07, and the χ^2 increases with 129.

4 Conclusions

First of all it was shown that continuous registration produced uncorrected results which indicated a clear downwards trend. This has been found not only in this panel, but in all panels mentioned previously. In fact, the reduction in registrations is so large that one cannot use such data without correction for the effects studied here.

It was also shown that the response burden had a significant effect on underreporting, zero-reportings and wave non-response. The latter does not automatically lead to a lower level in registrations, as we have already pointed out. For that, we must take a better look at (changes in) group compositions. Besides the burden, loyalty seems to play an important role in all three outcomes. This component of motivation requires further attention.

The adaptation of the model used by *Meurs et al.* (1989) made sense because of the large effect of heterogeneity, but because the model is still very simple not all possible effects can be analysed.

One has to bear in mind that the effects found at the individual level cannot be perfectly compared with the effects found at the aggregate level. For such a comparison, the (changes in) group compositions must be taken into account. One of the factors influencing the group composition is attrition, since it changes the group-division with respect to panel-membership. Earlier studies have shown that there are important differences in registration behaviour between these groups[3]. Taking this into account would require models more complex than the model discussed here.

Appendix: Expenditure pattern

One way to find the expenditure pattern of households is to analyse response-behaviour. The assumption we have made is that a household with a given number of household members has a more or less constant expenditure volume per month. If, for example, a household with a certain number of household members reports once in two weeks, but these two registrations have the same volume as an average household of this size which reports in four weeks, then this household presumably shops only once in two weeks and the missing registrations should be interpreted as zeroes.

The procedure we use is to take a sub-sample consisting of all households that make non-zero responses in four consecutive weeks (for simplicity we call such a period a month). For these households, we regress the average weekly registrations on a power-function in household-size:

$$y_{iw} = \alpha RW_{iw}^{\beta} + \varepsilon_{i1}$$

The estimates we find in six months are very similar: $\hat{\alpha} = .4$; $\hat{\beta} = .5$. The expenditure of the other households is divided by this estimate of average per-week expenditure, and the weights found in this way are analysed: if the average weight of a household is considerably larger than one (say 1.75), this household is likely to be one that does not shop each week. In our sample of about 2000 households, we find some 40 households with a weight of more than 1.75, but only two of these seem candidates for this regular-but-not-weekly expenditure pattern. The other households either report twice as much *each* week, or report very irregular with one purchase with a very high weight, both producing a high average weight. We therefore conclude that zeroes and missing registrations can be treated quite similarly.

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