An exploration of the application of PLS path modeling approach to creating a summary index of respondent burden

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ABSTRACT
The potential effect on respondent burden is a major consideration in the evaluation of survey design options, so the ability to quantify the burden associated with alternative designs would be a useful evaluation tool. Furthermore, the development of such a tool could facilitate more systematic examination of the association between burden and data quality. In this study, we explore the application of Partial Least Squares path modeling to construct a burden score. Our data come from a phone-based, modified version of the Consumer Expenditure Interview Survey in which respondents were asked post-survey assessment questions on dimensions thought to be related to burden – e.g., effort, survey length, and the frequency of survey requests (Bradburn, 1978). These dimensions served as the latent constructs in our model. We discuss model development and interpretation, assess how the measured items relate to our latent constructs, and examine the extent to which the resulting burden scores covary with other survey measures of interest.

KEY WORDS: path modeling, respondent burden

1. Introduction

The Consumer Expenditure Survey (CE), sponsored by the U.S. Bureau of Labor Statistics, is currently undertaking a multiyear research effort to redesign the CE in order to improve data quality. The current Interview Survey instrument asks respondents to recall detailed out-of-pocket household expenditures over a 3-month reference period, a process acknowledged to be burdensome to the respondent. Since it is commonly assumed that respondent burden is associated with the quality of respondent reporting, the evaluation of survey design options should also take account of their potential effect on respondent burden.

In prior experiments of alternative survey design options, data on multiple indirect indicators of respondent burden were collected, but assessment of these indicators have typically taken the form of bivariate analyses, such as the comparison of the frequency distribution of these indicators among treatment groups, or cross-tabulations of these indicators with sample characteristics or other indicators of reporting characteristics. A summary measure of burden that is based on all these indicators would provide a way to rank the respondents on a "burden continuum," and thus allowing the investigation of how survey characteristics of interest change on this continuum.

2. The Study

The objective of this exploratory study was to learn to apply the methodology of partial least squares (PLS) path models to develop a summary index of respondent burden from multiple indirect indicators of burden. This exploratory research used data from a small-scale field test (Creech et al. 2011). The field test survey instrument was based on a shortened version of the ongoing Consumer Expenditure Quarterly Interview Survey, which collects detailed household expenditure information. One of the treatment conditions in this field test was designed to investigate the effect of a shortened reference period on the quality of expenditure reporting. The research reported in this paper is based on the final wave interview data from that treatment group (Recall) and the Control group in the field test. The Recall group was asked about their expenditures for a one-month reference period, and their survey panel consisted of 4 waves, with each interview taking place over 4 consecutive months. The Control group was asked to recall expenditures for a 3-month reference period, and their survey panel consisted of 3 waves, with each interview taking place three months apart. Data collection for both treatment groups began in June 2010, ending in November 2010 for the Recall group and February 2011 for the Control group.

The interviews were conducted by computer-assisted telephone interview (CATI). In each wave, respondents were asked about their purchases during the reference period on major appliances, clothing, vehicle operating expenses, non-health insurance, health insurance, education, subscriptions, trips, and average weekly expenses on food and beverage. At their end of their final interview, respondents were asked a series of post-survey assessment questions (PSAQs) about their survey experience: how burdensome they found the survey to be (PSAQ_3), their interest in survey content (PSAQ_1), their perception of difficulty in responding to the survey questions (PSAQ_2a), their perception about the length of the interview (PSAQ_4), the use of recall aids, the appropriateness of the frequency of survey requests (PSAQ_3a), and the appropriate number of contact attempts (PSAQ_3b). From the contact attempt history for the sample units, we identified sample units for whom refusal conversion assistance was requested at least once over their survey panel.

3. Methodology

3.1 Data

As noted above, the present analyses were conducted on the final wave interview data from the Recall and Control groups since the post-survey assessment questions are asked only in the final interview. The final wave response rate was 64.9 percent for the Control group (N eligible = 735) and 59.4 percent for the Recall group (N eligible = 1006).[1] A requirement of the software we used to perform our analyses required complete case data (i.e. there are no missing values on the items used in the model), so only respondents who provided valid answers to all the items used in the analysis were included in our study sample. Selected demographic characteristics of the study sample appear in Table 1. Differences in characteristics between the two groups were generally less than 3 percentage points, with the exception of respondents in the Recall group being more

[1] The response rate definition used was AAPOR response rate definition RR4 [see page 44, AAPOR(2011)], with the proportion of eligibility among cases with “unknown” final disposition assumed to be 0.33.

likely to be in the 35-64 age range, and more likely to have attained at least a High School degree.

3.2 Partial Least Squares Path Models

Partial Least Squares path modeling (PLS) is a multivariate data analysis technique that provides researchers the opportunity to simultaneously assess the measurement of the constructs (or latent variables – we use these terms interchangeably), and test hypotheses on all the relationships among the constructs within the same analysis. This technique is designed to explain variance, and is suited for predictive applications and theory-building. PLS performs an iterative set of factor analyses and ordinary least squares regressions until the difference in the average R^2 of the constructs become non-significant (p.27 in Gefen et al. 2000). It should be noted that some researchers consider PLS to be one type of structural equation modeling (SEM), while other researchers contend that PLS is a form of regression and not "mainstream" SEM (e.g. Rouse and Corbitt 2008), which is based on analysis of covariance structures that explicitly models measurement errors.

Assumptions. The PLS technique imposes less stringent assumptions on normality of the data and measurement scales than covariance-based structural equation model (SEM) methods. It can be applied to small samples, accommodate both reflective and formative measurement models, and contain many constructs and indicators without leading to estimation problems (p.279-281, Henseler et al. 2009). However, the technique assumes the relationship between the observed variables and their constructs is linear. And although PLS has low sample size requirements, it may not have an advantage in detecting statistical significance in small sample sizes. In addition, PLS parameter estimates are asymptotically correct (large sample size and large number of indicators per latent variable; p.296, Henseler et al. 2009).

The PLS framework consists of two inter-related models: (1) the measurement model, which describes the assignment of the observed items (or indicators) to each unobserved construct , and (2) the structural model, which describes the relationship among the set of constructs. Both models are explicitly defined by the analyst, and depicted in a path diagram. The direction of relationships between a construct and its item pool (the indicators associated with a construct) can be described as a reflective or formative. With a reflective construct, the items are assumed to reflect variation in the construct; thus a change in the construct is manifested as a change in all its items. With a formative construct, it is assumed that the observed items represent different dimensions of the construct, and so the items need not be correlated with each other. For our objective of constructing an index of respondent burden, we used a formative measurement model.

Algorithm. We performed the PLS analysis using the functions *plspm() and plspm.groups()* in the plspm package in R software (Sanchez and Trinchera 2012). The algorithm optimizes the explained variance (estimates R^2) of the endogenous latent variables, and uses bootstrapping to determine significance levels of estimated parameters. The key parameters estimated by the plspm algorithm are the item weights (i.e., the scalar coefficients in the linear equation relating the items to their associated latent variable), loading coefficients (i.e., the correlations between items and their associated latent variable), and path coefficients (i.e., the estimated coefficients of the structural model). For detailed discussions on how the algorithm produces the estimated parameters, see Sanchez (2009) (also Hensler et al. 2009).

Model assessment. PLS path modeling lacks a well-identified global optimization criterion, so there is no global fitting function to assess the goodness-of-fit criterion of the model (Vinzi et al. 2010). Instead, different criteria are used to assess partial model structures. A systematic application of these criteria involves first assessing the measurement model, then the structural model (Henseler et al. 2009, p.298). In the assessment of the measurement model, different criteria are used for reflective and formative constructs due to the different nature of the relationship between the items and the construct intended for measurement. For formative measurement model (the focus of our analyses), the criteria for validity at the item level are that item weights should attain statistical significance, and there should not be multicollinearity of items within an item pool (Henseler et al. 2009, p. 298-304). At the construct level, the formative index should have external validity (i.e. explain a large proportion of the variance of an alternative reflective measure of the focal construct), and nomological validity (i.e. the relationships between the formative index and other constructs in the path model that are known from prior research should be significant). For the structural model, the constructs should be distinct (cross-correlations between latent variables should be less than 0.5), the proportion of variance (R^2) for the endogenous construct should be at least 0.1, and the path coefficients should be significant.

3.3 The structural model

We adopted Bradburn‟s (1978) seminal research on factors that contribute to a respondent‟s perception of survey burden as the basis of our structural model. Bradburn identified four dimensions of burden: (1) length of the interview, (2) amount of effort required by the respondent, (3) amount of stress experienced by the respondent, and (4) the frequency with which the respondent is interviewed. In addition to underscoring the multidimensional nature of respondent burden, Bradburn emphasized that "burdensomeness" is a subjective characteristic of the task, "the product of an interaction between the nature of the task and the way it is perceived by the respondent" (pg. 36). As the nature of the question answering task becomes more difficult, all things being equal, the task may be perceived as more burdensome. Conversely, as positive elements of the task (e.g., interest in the survey topic or perceived importance of the data) become more salient, the task may be perceived as less burdensome. Fricker et al. (2011) used recursive partitioning analysis on data from the same field study to classify sample units in the Recall group into homogeneous groups according to their responses to post-survey questions about the burden dimensions. They found that respondents‟ perception of survey length was the dimension most strongly associated with reported burden, followed by respondent‟s interest in survey content, and the frequency of interview requests ("too many" pre-interview calls) and respondents‟ perceived difficulty in responding to survey questions were the next dimensions associated with reported burden.

In our study data, we have indicators for three of the four dimensions of respondent burden (PB): perception of survey length (PL), perception of effort (PE), and perception of frequency of the interview requests (PF). Taking account of the findings by Fricker et al. (2011), we posited the following two endogenous relationships in the structural model for PLS analysis:

1. Perception of survey burden: we hypothesize that perceived length of the survey (PL), perceived effort (PE), and perceived frequency of survey request (PF) influence a respondent‟s perception of survey burden (PB).

$$PB = \beta_{eb} PE + \beta_{fb} PF + \beta_{lb} PL$$

2. Perception of survey length: in addition, if a respondents needs to exert more effort to respond to survey questions, this may lead him/her to perceive it takes a longer time to complete the interview. Similarly, the frequency of survey requests and/or the attempts to contact a sample unit to conduct the survey could increase the saliency of the survey, which may in turn exaggerate any negative perceptions the respondent already has about taking the survey – such as the length of time it takes to complete the survey. Thus, the amount of effort a respondent exerts, and the frequency of survey requests made of the respondent could both influence the respondent‟s perception of survey length.

$$PL = \beta_{el} PE + \beta_{fl} PF$$

3.4 Measurement model

A description of the items for the constructs in the structural model appears in Table 2. The constructs are the burden dimensions, PL, PE, PF, and PB. All the items were treated as formative indicators in the measurement model since they represent different dimensions of the respondent burden construct, and we use them to construct the respondent burden index. The frequency distributions of the items are shown in Table 3. The scale mean of categorical variables (mean for continuous variables) and standard deviations are presented in Table 4. For the analysis, the item data were standardized to mean of 0, variance of 1.

3.5 Burden index

We define the respondent burden index as a value assigned to a respondent that represents the degree to which he or she perceives burdened from the survey experience, where perceived burden is "measured" by the relationships specified in the structural model in section 3.2. Having obtained the scores of the exogenous latent variables from the measurement model, and the estimated path coefficients of the structural model for the Control-Recall data, the burden index for each respondent i, pb_man_i, was computed as a linear combination of the estimated path coefficients and the respondent‟s latent variable scores based on the two endogenous relationships for PB and PL:

$$\begin{aligned} pb\_man_i &= \beta_{EB} * Score_{PE,\,i} + \beta_{FB} * Score_{PF,\,i} + \beta_{LB} * Score_{PL,\,i} \\ &= \beta_{EB} * Score_{PE,\,i} + \beta_{FB} * Score_{PF,\,i} + \beta_{LB} * (\beta_{EL} * Score_{PE,\,i} + \beta_{FL} * Score_{PF,\,i}) \\ &= (\beta_{EB} + \beta_{LB} * \beta_{EL}) * Score_{PE,\,i} + (\beta_{FB} + \beta_{LB} * \beta_{FL}) * Score_{PF,\,i} \end{aligned}$$

4. Findings

4.1 Model assessment

The loading of each item with its associated latent variable (shown in bold) and its cross loading on other latent variables are shown in Table 5. An item"s loading on its associated latent variable is greater than its cross-loading on other latent variables in the model, which provides some evidence for construct validity. The weights of the items, with the exception of f1numatm, were all significant (Table 6). The correlation between items for item pools with only 2 indicators (e1int, e2ease) did not exceed 0.15, and the estimated magnitudes of multicollinearity for item pools with more than 2 indicators, (f1numatm, f2numwave, f3numatmp) and (l2timest, l3size, l4timep), computed as the mean of variance inflation factors, were less than 1.2, indicating that multicollinearity among items was not a problem. Taken together, these results indicate that the measurement model is valid. The cross-correlations between the latent variables were all less than 0.5 (Table 7), the estimated path coefficients were all significant ($p<0.05$), and the R^2 for both endogenous latent variables, perceived length and perceived burden, were greater than 0.1. The path model diagram, with the estimated item weights and path coefficients are shown in Figure 1.

4.2 Impact of Treatments on Burden

Having obtained the scores of the exogenous latent variables from the measurement model and the estimated path coefficients of the structural model for the Control-Recall data, the burden index pb_man_i was computed. The histograms of the burden index by treatment group are shown in Figure 2. The histograms suggest that there may be relatively more respondents with higher index values in the Recall group. Results from a Wilcoxon-Mann-Whitney test confirm what was visually apparent: the distribution for the Recall group is shifted right; burden index values were generally higher for the Recall group than the Control group ($W = 125355.5$, $p=0.0281$, 1-tailed test).

In addition, the PLS path model analyses also provides insights into how the groups differ on the paths in the structural model of perceived burden. The estimated path coefficients for the structural model depicted in Figure 1 are shown on the left panel of Table 8, and the path coefficients by treatment group appear in the right panel of Table 8. These results indicate that the perception of frequency (PF) had a smaller effect on perception of length (PL) for the Control group than it did for the Recall group (difference -0.17, $p=0.0190$), but there were no other differences between the groups on the other path relationships in the structural model.

4.3 Burden and Survey Outcomes

We also examined the distribution of the respondent burden index by selected panel survey characteristics of interest. The distribution of the burden index for intermittent respondents is shifted right relative to the distribution for respondents who completed all waves of the survey request (see left panel of Figure 3, $W=108543.5$, $p<0.0001$, 1-tailed test). The distribution of the burden index of respondents who had at least one refusal conversion noted in their contact attempt history is shifted right relative to the distribution of respondents who had none (see right panel of Figure 3, $W = 47242.5$, $p = 0.0009$, 1-tailed test). However, there was no evidence of an association between the burden index with total expenditures and prevalence of refusal or don"t know reports –

two indirect indicators of data quality typically used by the Consumer Expenditure Survey Program.

5. Discussion

The results of this exploratory study suggest that the PLS path modeling approach to constructing a burden index is promising: it not only permits construction of the index, but it also can provide insights into how different treatment conditions may differentially affect burden dimensions. This is useful information when considering which features to target for intervention in an ongoing survey or in a survey redesign, and for evaluating the impact of those changes.

As with any exploratory research, our study had a number of limitations, and in the process of conducting our analyses and examining the results, we learned valuable lessons that will improve future work in this area. First, when we examined the distribution of our burden index, we noticed that respondents tended to be chunked at regular intervals rather than dispersed evenly along a burden continuum. One potential reason for this is that the range and diversity of the burden index values is a function of the number of different covariate patterns possible among the indicators used in the measurement model. The relatively limited range of the index values and their lack of „smoothness‟ may be problematic in that the index values may not sufficiently differentiate between respondents across a "burden continuum" if we are trying to study the association of burden with a relatively large variety of survey measures of interest. We plan to extend our PLS path modeling approach in the future by incorporating an expanded set of items related to the different dimensions of burden.

It also is important to systematically develop and test the burden items that you intend to serve as the basis of a summary index of the latent „burden‟ construct. As we noted earlier, the burden items used in this study were taken from an existing dataset, and many of the items were based on questions used in the empirical burden literature. Additionally, we examined but found no evidence for collinearity among our indicators. However, a full item development process would ideally involve some activities which we did not perform – e.g., pre-testing items to assess content and indicator specification, expanded testing of external validity, etc. (see, e.g., Arnett et al., 2003, or Helm, 2005). As such, it is unclear the extent to which our items covered the burden construct, so inferences from the model described in Section 4 should be viewed primarily as illustrative of working through the PLS methodology.

Finally, our model specification and our substantive interpretations of the results were somewhat influenced by our choice of analytic methods and tools. For example, we decided to use the plspm package in R because it offered many advantages over other programs: it is free; the barriers to entry are low (coding is straightforward and flexible, documentation is available, etc.); and it can be used with all of the other R data analysis options. However, other software for implementing PLS path modeling (e.g. SmartPLS) may permit investigations of other features of this approach that were not available in the plspm package (e.g. exploring a model in which there is only one latent variable - burden - as in Helm, 2005). Additionally, the application of other data reduction methods to the analysis of burden-related items certainly merits further investigation. However, the results of this study illustrate the potential advantages of these approaches generally to better understanding conceptualizations and measures of respondent burden, which will ultimately aid its management and reduction.

Table 1. Selected sample characteristics of study sample

Characteristic	Control	Recall
N	431	543
Respondent age group		
missing	0.5	0.4
<25	3.3	3.5
25-34	59.2	53.8
35-64	36.0	41.4
65+	1.2	0.9
Respondent Education attainment		
missing	0.7	0.7
Less than High School	6.5	7.2
High school graduate	21.6	24.9
Some college	29.2	26.9
Undergraduate	24.6	20.8
Postgraduate	17.2	19.5
Respondent‟s race (respondent can identify with more than one race)		
White	88.6	89.3
Black	7.4	5.5
Hispanic origin		
missing	0.7	0.6
1	6.5	6.5
2	92.8	93.0
CU size		
1	26.9	26.7
2	37.1	39.4
3+	36.0	33.9
Housing tenure		
Owner	89.6	92.1
Rent	8.6	6.5
Other	1.9	1.5

Table 2. Measurement model: indicators used for respondent burden dimensions

Item	Variable name in analysis	Question & response options
Dimension: perceived length (PL)		
Perceived survey length (final wave)	l4timep	Do you feel that the length of today's interview was too long, too short, or about right? 1= too short; 2= about right; 3= too long
Household size	l3size	Number of members in the household
Estimated time (final wave)	l2timest	How long do you think today's interview took? Response in minutes
Dimension: perceived effort (PE)		
Interest in survey topic	e1int	How interesting was this survey to you? 1=very interested; 2=somewhat; 3=not very; 4=not at all
Perceived ease in responding to survey questions	e2ease	How difficult or easy was it for you to answer the questions in this survey? 1=easy; 2=some easy; 3=some difficult; 4=very difficult
Dimension: perceived frequency (PF)		
Number of contact attempts	f1numatm	Number of contact attempts recorded in the contact history for the sample unit
Perceived appropriateness of number of contact attempts	f3numatmp	Thinking about the number of phone calls you received before each interview, would you say that it was too many, or did it seem like a reasonable number? 1=Reasonable; 2=Too many
Perceived appropriateness of number of survey requests in survey panel	f2numwave	Over the course of the survey, you were asked to participate in (3 interviews for CON group, and 4 for REC group) interviews. Would you say that this was too many interviews, or did it seem like a reasonable number? 1=Reasonable; 2=Too many
Dimension: perceived burden (PB)		
Perceived burden (final wave)*	b1burdenp	How burdensome was this survey to you? 1= not at all burdensome; 2= not very; 3= somewhat; 4= very

* Typically, there should be more than 1 indicator for a latent construct, and all facets of the construct should be covered by indicators (although it is not necessary for every facet to be measured by multiple indicators – Helm (2005), p. 100). For the Perceived Burden dimension, we were constrained by the number of indicators available for each dimension in the analysis.

Table 3. Items used in PLS analysis: frequency distribution of scaled items

ITEM	CONTROL (n=431)	RECALL (n=543)
e1int		
1=very interested	21.1	16.6
2-somewhat	52.4	49.9
3=not very	16.2	19.2
4=not at all	10.2	14.4
e2ease		
1=easy	44.6	53.0
2=some easy	38.3	35.2
3=some difficult	15.8	10.1
4=very difficult	1.4	1.7
f2numwave		
1=reasonable	67.5	58.0
2=too many	32.5	42.0
f3numatmp		
1=reasonable	71.0	69.2
2=too many	29.0	30.8
l4timep		
1=too short	0.2	1.3
2=about right	82.8	78.5
3=too long	16.9	20.3
b1burdenp		
1=not at all burdensome	34.3	26.3
2=not very	29.5	28.6
3=somewhat	31.3	37.8
4=very	4.9	7.4

Table 4. Items used in PLS analysis: scale mean, means, and standard deviations

	Control (n=431)		Recall(n=543)	
ITEM	Mean	SD	Mean	SD
e1int	2.2	0.9	2.3	0.9
e2ease	1.7	0.8	1.6	0.7
f1numatm*	5.7	5.6	5.5	5.4
f2numwave	1.3	0.5	1.4	0.5
f3numatmp	1.3	0.5	1.3	0.5
l2timest*	20.7	11.7	18.2	8.6
l3size*	2.5	1.4	2.4	1.4
l4timep	2.2	0.4	2.2	0.4
b1burdenp	2.1	0.9	2.3	0.9

* indicates mean of integer variables; otherwise, mean of scale for categorical variables are shown.

Table 5. Item loadings and cross loadings

Item	PE	PF	PL	PB
e1int	**0.85**	0.36	0.25	0.43
e2ease	**0.65**	0.15	0.23	0.30
f1numatm	0.08	**0.30**	0.07	0.13
f2numwave	0.32	**0.82**	0.27	0.32
f3numatmp	0.27	**0.84**	0.24	0.35
l2timest	0.14	0.07	**0.40**	0.16
l3size	0.05	0.06	**0.23**	0.10
l4timep	0.30	0.31	**0.95**	0.30
b1burdenp	0.49	0.40	0.33	**1.00**

Bolded numbers are loadings of each item with its associated construct

Table 6. Estimated item weights

Latent variable	Item	Weight	95LCI	95UCI
Perceived effort (pe)	e1int	0.77	0.69	0.84
	e2ease	0.53	0.44	0.63
Perceived frequency (pf)	f1numatm	0.02	-0.10	0.13
	f2numwave	0.57	0.48	0.69
	f3numatmp	0.62	0.50	0.72
Perceived length (pl)	l2timest	0.21	0.07	0.35
	l3size	0.20	0.10	0.32
	l4timep	0.90	0.82	0.97
Perceived burden (pb)	b1burdenp	1.00	1.00	1.00

Bootstrapping was used to compute significance of estimated weights.

Table 7. Correlations between latent variables

	pe	pf	pl	pb
pe	1.00			
Pf	0.36	1.00		
pl	0.31	0.31	1.00	
pb	0.49	0.40	0.33	1.00

Table 8. Estimated path coefficients for the structural model

Overall (combined data)					By group			
Path	Control and Recall (C + R)	SE	95LCI	95UCI	Control (C)	Recall (R)	Difference (C – R)	P - value
pe->pl	0.22	0.04	0.17	0.28	0.26	0.22	0.04	0.5704
pe->pb	0.37	0.03	0.32	0.42	0.40	0.34	0.06	0.2587
pf->pl	0.23	0.04	0.17	0.29	0.13	0.30	**-0.17**	**0.0190**
pf->pb	0.22	0.03	0.17	0.28	0.25	0.19	0.06	0.3167
pl->pb	0.15	0.03	0.09	0.19	0.16	0.17	-0.01	0.9401

Standard errors and confidence intervals computed through bootstrapping.

Figure 1. Estimated item weights and path coefficients

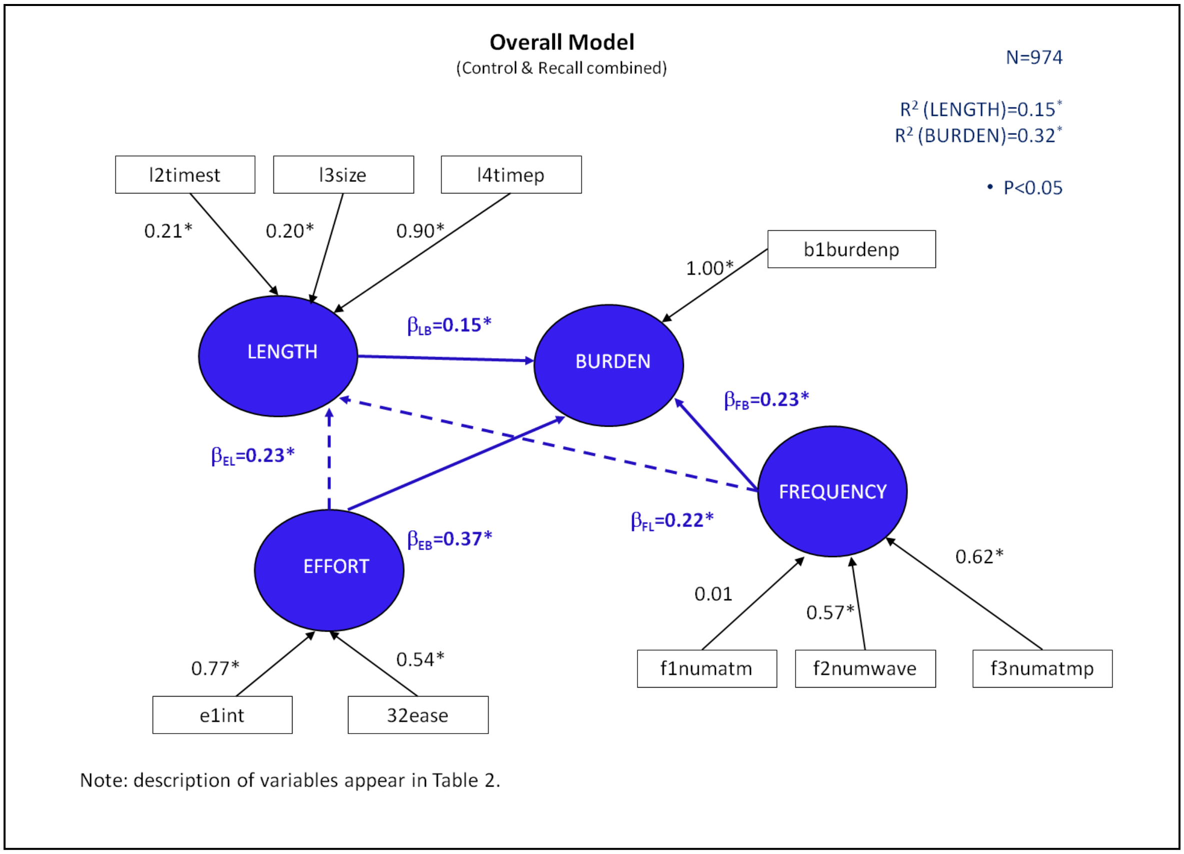


Figure 2. Histogram of the respondent burden index by treatment group

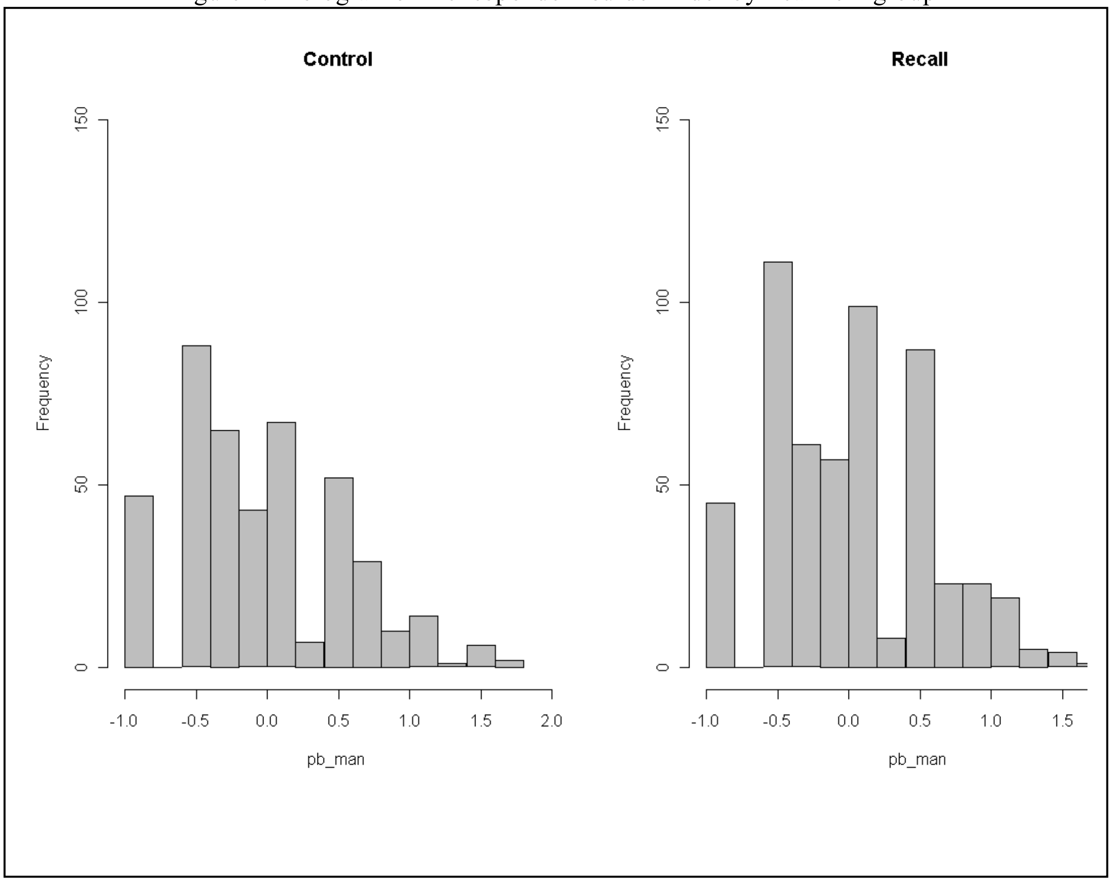
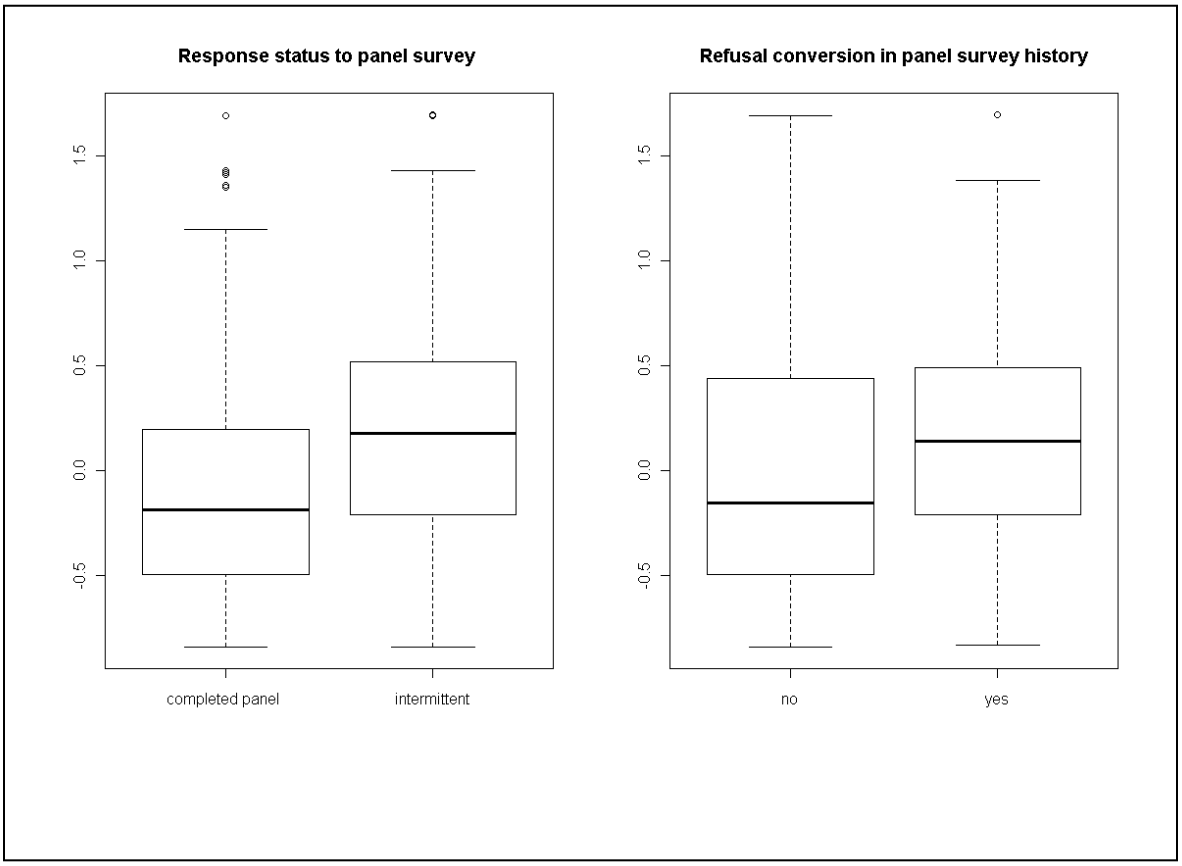


Figure 3. Distribution of respondent burden index by selected survey panel characteristics



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