Using Doorstep Concerns to Characterize and Assess the Level of Reluctance of Survey Respondents October 2012

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Abstract
As household surveys are experiencing declining response rates in the past few decades, reducing nonresponse and correcting for potential nonresponse error have been two major challenges for survey organizations. Doorstep concerns – one type of paradata – capture the interactions between interviewers and potential survey respondents during the survey introduction and reveal the concerns sampled members have expressed about the survey request and also their reasons for refusing the survey request when refusal occurs. Different organizations collect doorstep concerns in different ways. One challenge has always been how to best use and analyze these data given the inherent organizational design and collection constraints. This paper demonstrates two different ways of using doorstep concerns to characterize and to assess the reluctance of survey respondents – principal component analysis (PCA) and latent class analysis (LCA). We found that both methods produce parsimonious measures indicative of respondents' reluctance level and the two measures are correlated with each other.

Key Words: paradata, doorstep concerns, nonresponse, principal component analysis, latent class analysis

1. Introduction

Household surveys have experienced declining response rates in the past few decades (Curtin et al., 2000; Atrostic et al, 2001). The declining response rates have driven up the cost of data collection (due to the extra effort and money invested to contact and recruit reluctant sample members) on the one hand and increased the risk for nonresponse bias when nonresponding sample members are systematically different from responding sample members in key statistics of interest on the other. As a result, reducing nonresponse and correcting for potential nonresponse bias have been two major challenges for survey organizations.

Sample members' decision to participate in a household survey is largely situational and the interactions between sample members and interviewers during the survey introduction are very critical and influential in sample members' participatory decisions (Groves and Couper, 1998). Doorstep concerns are one kind of paradata that capture such interactions and reveal concerns sample members have expressed about the survey request. They have been used for three purposes – studying survey participation, tailoring follow-up strategies, and examining response quality (Kreuter and Olson, 2012).

Post-hoc analyses of doorstep concerns data have demonstrated that respondents who have expressed privacy concerns, time-constraints concerns, and general negative statements such as “I’m not interested” have lower cooperation rates than those without these concerns (Campanelli et al., 1997; Dalhamer and Simile, 2009; Groves and Couper, 1998; Bates et al., 2008; Safir and Tan, 2009). Those respondents with more concerns tended to have lower likelihood to agree to the survey request than those with fewer concerns (Tan and Tsai, 2008; 2011; Tsai and Tan, 2010). By contrast, respondents asking questions about the survey at the introduction had better cooperation rates than those who did not ask questions (Groves and Couper, 1996).

A few papers looked into the associations between the types of concerns survey respondents have expressed at the outset and the quality of their responses to the survey questions (Campanelli et al., 1997; Couper, 1997; Dalhamer, Simile, and Taylor, 2008). Mentions of “not interested” are found to be associated with less time spent on the questionnaire (Dalhamer, Simile, and Taylor, 2008) and higher item missing rates (Campanelli et al., 1997; Couper, 1997; Dalhamer, Simile, and Taylor, 2008).

Doorstep concerns data have also been analyzed to propose tailored persuasion strategies and/or interviewer languages (Campanelli and Klassen, 2009; Campanelli et al., 1997; Groves and McGonagle, 2001).

Survey organizations vary in how they collect doorstep concerns data and how much they collect. Actual interactions between interviewers and respondents at the survey introduction are sometimes taped or recorded for further coding and content analysis (e.g., Campanelli et al., 1997 and Maynard and Schaeffer, 1997). The key challenge with this type of data collection method is the qualitative nature of the resulted data, which makes the data harder to process and to analyze.

Alternatively, interviewers are instructed to answer scripted questions about the type of concerns respondents have expressed during the introduction at the end of each contact (e.g., Couper 1997). One example is the Contact History Instrument (CHI) implemented and used by the Census Bureau (For a detailed description, see Tan, 2010 and Bates et al., 2008). The CHI is a standard-alone Blaise instrument. Interviewers are trained to make a CHI record for each contact attempted with a sampled household. Besides basic information such as date and time of the contact, outcome of the contact, and strategies adopted by interviewers, interviewers are required to check (on a computer screen) one or more categories off a list of 21 verbal or nonverbal concerns that can be expressed by respondents during the survey introduction and interactions. A screenshot of the doorstep concerns screen is displayed in Figure 1.

Given the amount of details embedded on this screen, researchers have approached and analyzed this screen in many different ways. For instance, Bates and colleagues first rolled up the contact-level doorsteps concern data to household-level data. Then they created one summary measure indicating the number of unique concerns the sampled household had expressed as well as 17 dichotomous variables with each indicating whether a sampled household had expressed a particular type of concerns over the course of data collection (Bates et al., 2008). [1] Restricting to concerns given at the first contact, Dalhamer and colleagues (2008) created three dummy concern variables indicating whether or not a sampled household mentioned “not interested,” “too busy,” and “privacy

[1] They dropped 4 concerns relevant only to longitudinal surveys in their analyses.

concerns" at the first contact. The disadvantage of the summary measure Bates and colleagues created is the loss of information. For instance, the summary measure doesn't include information on what concerns a sampled household has mentioned and for how many times over the period of data collection. By contrast, the disadvantage of creating a dichotomous variable for each specific mention of concerns is that the interrelationships between concerns are ignored.

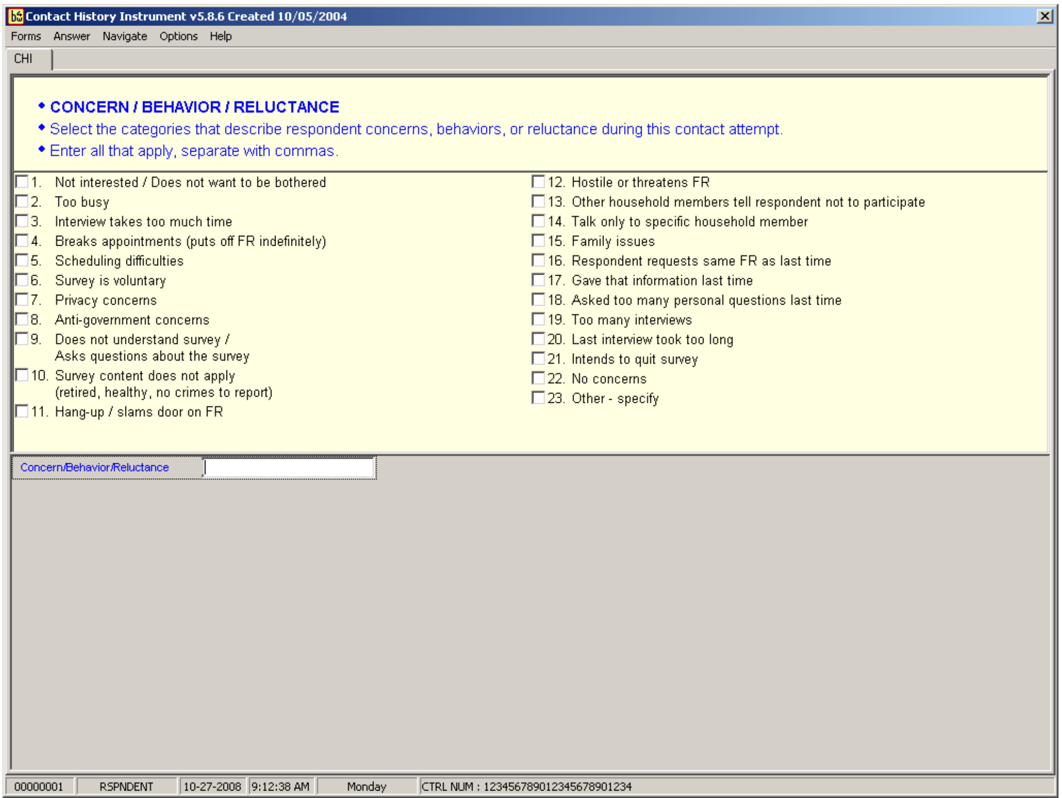


Figure 1: Screenshot of the Contact History Instrument Used by the Census Bureau.

In a later paper, Dalhamer and Simile (2009) first did a factor analysis on all mentions of concerns and four factors were extracted – "gate-keeping concerns," "hostility/hard refusal," "survey content/privacy," and "time constraints" (see Figure 1 on p265). They then created four dichotomous measures to indicate whether respondents had expressed one or more concern related to "gate-keeping concerns," related to "hostility/hard refusal," related to "survey content/privacy" concerns, and related to "time constraints" separately. In a footnote, they noted that using factor scores from the factor analysis (instead of the four summary dichotomous variables) didn't change their conclusions. We believed that Dalhamer and Simile's summary measures retained the interrelationships between individual concerns. However, when entering all four summary measures into a regression model, for instance, they might still cause multicolinearity.

Tan and Tsai examined doorstep concerns data collected through CHI for the Consumer Expenditure Interview Survey (Tan and Tsai, 2008; 2011; Tsai and Tan, 2010). [2] They did a principal component analysis and generated an index as the weighted sum of the

[2] Bates et al. (2008), Dalhamer and Simile (2009),and Dalhamer, Simile, and Taylor (2008) all used doorstep concerns data collected via CHI for the National Health Interview Survey.

principal component scores. Higher values on this index indicate higher or more concerns a sampled household had with the survey request. They found that sampled households with higher index values had lower likelihood to participate in the Consumer Expenditure Interview Survey and lower data quality than those with lower index values (Tan and Tsai, 2008; 2011; Tsai and Tan, 2010).

This paper extends the work by Tan and Tsai and attempts to systemize the analysis of doorstep concerns data collected via CHI. We have two goals in this paper: 1) To demonstrate how principal component analysis (PCA) and latent class analysis (LCA) can be used on doorstep concerns data to characterize the level of reluctance in survey respondents, and 2) To evaluate the effective of the two methods in assessing reluctance levels.

2. Principal Component Analysis (PCA) and Latent Class Analysis (LCA)

2.1 Principal Component Analysis (PCA)

Principal components analysis (PCA) is a multivariate statistical method to reduce the number of variables in a data set into a smaller number of dimensions. As Tan and Tsai (2010, 2011), we used PCA to reduce the 22 dichotomous concerns variables to a simpler data structure of lower dimensionality so that relationships between perceived concerns are directly revealed. The new smaller set of variables is principal components, where each principal component is a linear weighted combination of the original perceived concern variables.

Of greater interest and relevance to this paper is the construction of a Perceived Concerns Index (PCI) for each sampled household as an overall ordinal measure of the extent of concerns a sampled household might have. We define PCI as a weighted sum of the principal component scores. As shown in Equation 1, a principal component score, PC_{ij}, for each sampled household is a weighted combination of the actual perceived concern variables, where the weights are the factor loadings.

$$PC_{ij} = \sum f_{jk} X_{ik} \qquad 1)$$

PC_{ij} is the j^{th} principal component score for the i^{th} sampled household and X_{ik} is the k^{th} dichotomous concerns variable collected via CHI for the i^{th} sampled household. f_{jk} is the factor loading of the dichotomous concerns variable k on the j^{th} principal component score.

Then, we calculate a PCI for each sampled household using Equation 2:

$$PCI_i = \sum_{j=1}^{R} w_j PC_{ij} \qquad 2)$$

where PCI_i is the PCI score for the i^{th} sampled household and w_j is the weight of the j^{th} principal component score and equals to inverse of the proportion of variance explained by PC_j. Sampled households with a higher PCI score are interpreted as having more concerns about the survey relative to sampled households with a lower PCI score.

2.2 Latent Class Analysis (LCA)

Latent Class Analysis (LCA) is a categorical analog to factor analysis. It models the relations among a set of observed categorical indicator variables by assuming one or more categorical latent variables. LCA estimates two types of population parameters: 1) the prevalence of each latent class, the number of which the analyst can specify a priori, and 2) the probabilities, conditional on latent class membership, that an individual will demonstrate a specific response to an observed variable.

Assume there are K latent classes from J observed dichotomous doorstep concerns variables. Let $x = (r_1,\ldots r_J)$ represent the vector of a particular sample household's responses to the J concerns variables. Each doorstep concerns variable j has two response categories – $r_j=1$ if the sampled household didn't mention that particular concern and $r_j=0$ if the sampled household did mention that particular concern. Let C represent the latent variable with K latent classes. In addition, an Indicator function, $I(x_j = r_j)$ is also introduced. $I=1$ when the response to variable j equals to r_j and otherwise $I=0$.

Given the above notations, the probability of observing a particular response pattern can be expressed as follows:

$$\Pr\{X = x\} = \sum_{c=1}^{K} \gamma_c \prod_{j=1}^{J} \prod_{r_j=1}^{2} \rho_{j,r_j|c}^{I(x_j=r_j)}, \quad (3)$$

where γ_c is the probability of membership in latent class **c** and $\rho_{j,r_j|c}^{I(x_j=r_j)}$ is the probability of response r_j to variable j given membership in latent class c.

Of greater interest to us is the individual's probability of membership in each latent class, which can be computed by applying Bayes's theorem:

$$\Pr\{C = c \mid X = x\} = \frac{\Pr\{C = c\} * \Pr\{X = x \mid C = c\}}{\Pr\{X = x\}} = \frac{e^{\beta_{0c}+\beta_{1c}x}}{1 + \sum_{c'=1}^{K-1} e^{\beta_{0c'}+\beta_{1c'}x}}. \quad (2)$$

We then assign a sampled household to specific latent class based on their highest posterior class membership probability.

3. Data

For this paper, we used CHI data collected by the Census Bureau for Consumer Expenditure Quarterly Interview Survey (CE) sponsored by the Bureau of Labor Statistics. CE is a longitudinal a household survey measuring expenditure. It employs a rotation panel design and sample households will be interviewed up to five times once recruited. Wave 1 is used for bounding purposes and data from waves 2 to 5 are used to produce expenditure estimates. In the 2009 CE Interview Survey, there were 47,609 eligible housing units, from which 35,756 usable interviews were collected, resulting in a response rate of 75.1 percent (BLS).

CE started collecting CHI since 2005. Interviewers are required to enter a CHI record at the end of each contact. As shown in Figure 1, a total of 21 categories of concerns are listed on the screen together with "no concern" and "other (specify)." For this paper, we looked at CHI data collected from Q2 of 2005 to Q4 of 2009. Displayed in Table 1 are total numbers of sampled households with CHI information by wave (aggregated across quarters) and, among them, the proportions who mentioned at least one concern throughout the data collection period.

Table 1. Total Sample And Number (and Proportion of) Sample with At Least One Concern

	Total Sample	Number (Proportion) with At Least One Concern
Wave 1	42,004	21,065 (50%)
Wave 2	40,865	20,898 (51%)
Wave 3	40,438	20,236 (50%)
Wave 4	40,006	19,506 (49%)
Wave 5	40,162	18,525 (46%)

4. Results

We first present results of principal component analysis, followed by results from LCA. Evaluation of the two methods is shown last.

4.1 PCA Results and Perceived Concerns Index (PCI)

Principal component analysis was carried out on sampled households who mentioned at least one doorstep concern. Five factors are extracted as a result of the principal component analysis. Displayed in Appendix I are factor patterns drawing on first interview data. The factor patterns do not change whether or not we included cases with no doorstep concerns.

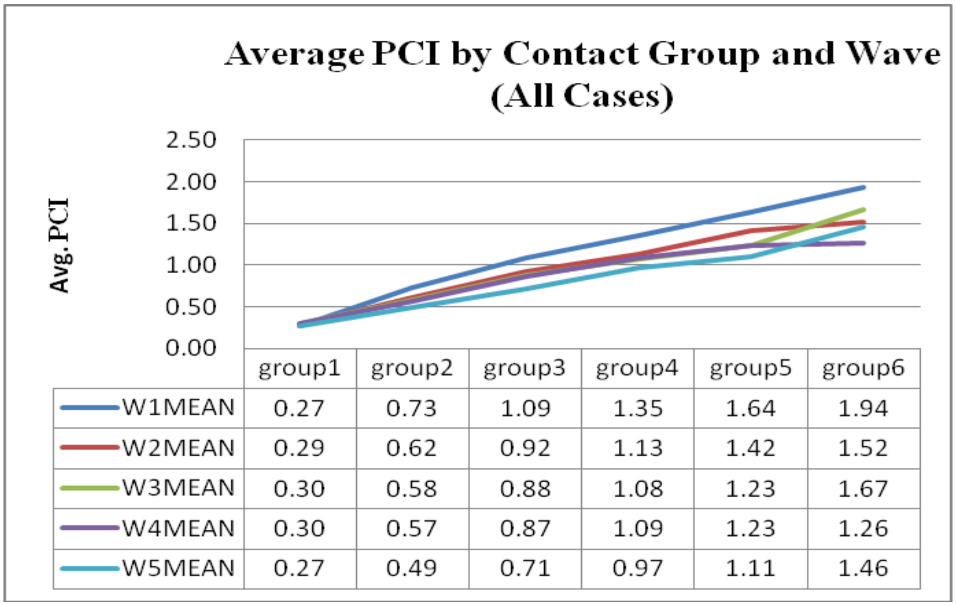
We then calculated PCI scores for cases with at least one door step concern based on Equation 2. Unlike Tan and Tsai (2010, 2011), we rescaled PCI scores so that the lowest value is 1 for better interpretation. Higher PCI values indicate higher or more concerns and, thus, higher resistance and reluctance exhibited by sampled households. Sampled households who did not mention any doorstep concerns were assigned a value of 0. Table 2 displays some univariate descriptive statistics on PCI scores by wave. The mean PCI values decrease by wave. In other words, resistance or reluctance seemed to have decreased the longer the sample members stayed in the panel.

Table 2. Univariate Distribution of PCI values by Wave

Wave	N	Mean	25th Percentile	Median	75th Percentile	Minimum	Maximum
Wave 1	42,004	0.55	0.00	0.04	0.78	0.00	11.22
Wave 2	40,865	0.47	0.00	0.18	0.66	0.00	10.98
Wave 3	40,438	0.45	0.00	0.12	0.63	0.00	12.96
Wave 4	40,006	0.44	0.00	0.00	0.61	0.00	11.03
Wave 5	40,162	0.37	0.00	0.00	0.50	0.00	15.79

Next we examined the relationships between PCI scores and traditional measures of sample member reluctance. We first grouped sample members based on the number of contacts required to recruit them. Sample members in Group 1 required 1-3 contacts and those in Group 2 required 4 to 6 contacts. Sample members in Group 3 required 7-9 contacts whereas Group 4 members needed 10 to 15 contacts. Group 5 cases needed 16 to 20 contacts and those in Group 6 required 21 or more. It is apparent that sample members in Group 1, on average, have a higher likelihood to be contacted than those in Group 6. The cut-off points for each group are chosen so that the groups are of the same sizes.

As displayed in Figure 2, the mean PCI values are the lowest for group 1 sample members and the highest for group 6 members regardless of which wave they are in. In general, groups that required more contacts have higher PCI scores than cases that needed fewer, suggesting that PCI is correlated with sampled households' contactability.



	group1	group2	group3	group4	group5	group6
W1MEAN	0.27	0.73	1.09	1.35	1.64	1.94
W2MEAN	0.29	0.62	0.92	1.13	1.42	1.52
W3MEAN	0.30	0.58	0.88	1.08	1.23	1.67
W4MEAN	0.30	0.57	0.87	1.09	1.23	1.26
W5MEAN	0.27	0.49	0.71	0.97	1.11	1.46

Figure 2. Mean PCI values by Contact Group and Wave

Next we divided sample members into one of two groups based on whether or not they expressed a refusal to either current wave of interview or any one of the earlier interview requests. It is clear from Table 3 that those who never refused have lower PCI scores on average than those who refused at least once; we interpret this to mean that the PCI scores are indicative of sample members' reluctance to participate in the survey.

Table 3: Mean PCI Values by Whether or not Sample Members Ever Refused to the Survey Request by Wave

Ever Refused?	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5
No	0.40	0.36	0.36	0.37	0.33
Yes	1.47	1.09	0.99	0.94	0.80

We further explored the relationship between PCI and the propensity to respond to the next wave. We divided wave 1 sample members into three groups based on their PCI scores. Those with no doorstep concerns are group 1 and those whose PCI scores are less than 3 are in group 2. Those with a PCI score bigger than 3 are in group 3. Naturally sample members in group 3 are more reluctant than those in group 2 and those in group 2 are more reluctant than group 1 cases. As shown in Table 4, there is a linear trend in terms of responses rates to later waves; cases in group 3 generally have a lower response rate to waves 2 to 5 than those in group 1 (The only exception to this linear trend is wave 2 response rates for group 2 and group 3 cases). It seems that PCI not only measures sampled households' reluctance to current wave's survey request but also predicts pretty well their reluctance to participate in later waves.

Table 4. Relationship between PCI and Propensity to Respond to Later Waves

Wave 1 PCI Grouping	% responded to Wave 2	% responded to wave 3	% responded to wave 4	% responded to wave 5
Group 1 (PCI= 0)	0.89	0.91	0.92	0.94
Group 2 (0 < PCI <= 3)	0.84	0.86	0.86	0.89
Group 3 (PCI>3)	0.86	0.83	0.85	0.86

4.2 LCA Results

We fit 2-class latent models on each wave separately. Tables 5 to 9 demonstrates class sizes as well as the average number of contacts required to complete the interview and the percent who ever refused to the survey request. It is clear from these tables that about a quarter of the cases fall into the "Difficult Respondent" class for all five waves. In addition, sampled households in the "Difficult Respondent" class on average needed more number of contacts and more of them had ever expressed refusal to the survey request than their counterparts in the "Easy Respondent" class. The latent class results are quite robust across waves.

Table 5: 2-Class Model for Wave 1 Cases

Latent Class	Proportion of Cases in this Latent Class	Mean Number Contacts Required	Percent Ever Refused to Survey Request
1 (Difficult Respondent)	25%	5.6	41.5%
2 (Easy Respondent)	75%	3.4	4.8%

Table 6: 2-Class Model for Wave 2 Cases

Latent Class	Proportion of Cases in this Latent Class	Mean Number of Contacts Required	Percent Ever Refused to Survey Request
1 (Difficult Respondent)	22%	4.8	44.8%
2 (Easy Respondent)	78%	3.4	8.8%

Table 7: 2-Class Model for Wave 3 Cases

Latent Class	Proportion of Cases in this Latent Class	Mean Number of Contacts Required	Percent Ever Refused to Survey Request
1 (Difficult Respondent)	21%	4.4	39.8%
2 (Easy Respondent)	79%	3.3	9.7%

Table 8: 2-Class Model for Wave 4 Cases

Latent Class	Proportion of Cases in this Latent Class	Mean Number of Contacts Required	Percent Ever Refused to Survey Request
1 (Difficult Respondent)	20%	4.2	35.4%
2 (Easy Respondent)	80%	3.3	9.2%

Table 9: 2-Class Model for Wave 5 Cases

Latent Class	Proportion of Cases in this Latent Class	Mean Number of Contacts Required	Percent Ever Refused to Survey Request
1 (Difficult Respondent)	17%	3.9	30.7%
2 (Easy Respondent)	83%	3.2	9.0%

4.3 Comparing PCA and LCA Results

Both the PCA and the LCA method are able to characterize sampled households on the level of the difficulty to contact and recruit them. We next examined whether or not results produced by the two methods are consistent. Specifically, we studied the mean PCI values for each of the two latent classes for every wave. As shown in Table 10, sampled households in the "Easy Respondent" class on average have lower PCI values than sampled households in the "Difficult Respondent" class across all waves. In addition, PCI values for the two latent classes are quite comparable across waves, suggesting that both methods are consistent and robust.

Table 10: Mean PCI values in Latent Classes by Wave

Latent Class	Wave1	Wave2	Wave3	Wave4	Wave5
1 (Difficult Respondent)	1.66	1.52	1.48	1.50	1.42
2 (Easy Respondent)	0.20	0.19	0.18	0.19	0.16

5. Conclusions and Discussion

This paper conducted principal component analysis and latent class analysis on doorstep concerns data collected via CHI. CHI is an independent Blaise instrument that must be entered by interviewers at the end of each contact attempt. Interviewers are required to check all concerns that the sampled households might have mentioned. Thus, by design, doorstep concerns data collected by CHI consist of 23 dichotomous variables. In this paper, we first analyzed the 23 dichotomous variables using principal component analyses and generated a Perceived Concern Index (PCI) for all sampled households with at least one concern throughout all possible contacts. The PCIs are rescaled to start from 1 and sampled households that didn't mention any concerns at the doorstep are assigned a value of 0. We found that PCI is highly indicative of the reluctance level exhibited by the sampled households; sampled households with higher PCI values are associated with more number of contacts, more refusals, and lower likelihood to participate in the later waves.

We also carried out 2-class latent models on these data. Across the five waves, about a quarter of sampled households fall into the "Difficult Respondent" class. Compared to those in the "Easy Respondent" class, sampled households in the "Difficult Respondent" class required more contacts and were more likely to refuse to the survey request.

Lastly, we examined the relationship between the two latent classes and PCI values across waves. Sampled households in the "Difficult Respondent" class had, on average, higher PCI values than those in the "Easy Respondent" class, suggesting that the results from the two methods are consistent with each other.

This is our preliminary attempt to systemize the analyses of CHI data. Our results are limited by the weaknesses of the CHI data as described by Bates and colleagues (Bates et al., 2008). In addition, our results are adequate only to the extent that the assumptions of both methods are met. However, we believe that both PCI and latent classes generated at the result of PCA and LCA are able to retain the interrelationships of the concerns data and are superior measures of reluctance level exhibited by sampled households than simple dichotomous measures for each of the concerns variables captured by CHI or simple summary measures that do not take into account the interrelationships of the concerns variables. We recommend survey practitioners to implement both methods in their analyses of CHI data and to test the feasibility and applicability of both methods in different survey contexts.

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