RESPONSE MODELS IN RDD SURVEYS: UTILIZING GENESYS TELEPHONE-EXCHANGE DATA

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Abstract

Households are increasingly using answering machines, call waiting, and other screening and call-blocking services. These popular innovations are significantly influencing how telephone surveys are conducted. For random digit dialing (RDD) household surveys, for example, the resolution of whether or not a number identifies a household is becoming more challenging. Likewise, obtaining household participation in a survey is becoming more difficult. Hence, not only are survey methods being revised, but also more effective methods are being sought to adjust for the lower rates of successfully screened numbers and completed responses.

This paper investigates the feasibility of using logistic regression models to predict for each sampled RDD number in a recently completed household survey setting, the likelihood of resolving the number and the likelihood, if the number is a household telephone number, that the household will complete the questionnaire. The RDD numbers in this example are generated through the Genesys system, which contains a substantial amount of auxiliary demographic information about households at the telephone-exchange level. We seek to use these auxiliary data in "propensity" models to adjust the sampling weights for nonresponse.

1. Introduction

a. Background

Households are increasingly using answering machines, call waiting and other screening and call-blocking services. These popular innovations are significantly influencing how telephone surveys are conducted. For random digit dialing (RDD) household surveys, for example, the resolution of whether or not a number identifies a household is becoming more challenging. Likewise, obtaining household participation in a survey is becoming more difficult. Hence, not only are survey methods being revised, but also more effective methods are being sought to adjust for the lower rates of successfully screened numbers and completed responses.

We use Genesys Sampling Systems to generate RDD numbers for many of our telephone surveys at Mathematica Policy Research, Inc. Hundred-blocks (i.e., 100 numbers identified by the first eight digits of a ten-digit telephone number: NPA-NXX-00xx) containing one or more listed telephone numbers are used to generate candidate telephone numbers; a list assisted method (Potter, et al 1991). These numbers are then checked using an auto-dialer to remove business and some nonworking numbers. The remaining numbers are assigned to the telephone centers for conducting the survey. Three issues are of concern: (1) some numbers cannot be resolved as to whether or not they are assigned to a household (assuming a household survey); (2) for those identified as households, the screening cannot be completed for some; (3) and for those screened in households, some do not complete the interview.

The use of logistic regressions to estimate response propensity has been widely used in a number of major survey settings. These have utilized explanatory information in the models from various sources, including sampling frame information, small-area statistics from the Census, the Area Resource File (county-level information from numerous sources), information from previous rounds in longitudinal surveys, and information about telephone-based areas such as telephone exchange and telephone "hundred blocks". The latter is the topic investigated in this paper. Further, the application of propensity models ranges from their use to identify weighting classes, which are then used to adjust sampling weights for nonresponse, to using the model predictions themselves to directly adjust the weights of respondents. Here we use the model predictions themselves to adjust sampling weights.

Related Applications

A literature review of the applications of propensity modeling or methods to adjust for nonresponse is not presented here. But we mention some directly related studies and one recent example of an application of propensity models to form weighting class cells.

Resolvability, Screening, And Response Models In RDD Surveys: Utilizing Genesys Telephone-Exchange Data

This paper by the same authors (Lu, Hall and Williams, 2002), investigates the feasibility of using logistic regression models to predict for each sampled RDD number in a recently completed household survey setting, the likelihood of resolving the number and the likelihood, if the number is a household telephone number, that the household will complete the screening questions, and finally that the household will complete the questionnaire. This was an RDD survey, recently conducted by MPR, of New

Jersey residents, age 18 and older. The sample was selected within five geographic strata in New Jersey. A total of 35,909 RDD numbers were assigned to telephone interviewers, but about 28 percent could not be resolved. This results in uncertainty about the number of eligible households in the study population and important inference domains. Further, about 35 percent of identified households did not complete a screener and 20 percent of the screened households did not complete an interview. These results, while not unusual for telephone surveys, are potential sources of survey bias.

The methodology used there is basically the same as in the current paper except that study was based on the results of an RDD survey in a single state. The current study extends the investigation to a large national sample, and selected communities in that survey, a broader setting and more complex design.

The RDD numbers in this example were generated through the Genesys system, which contains a substantial amount of auxiliary demographic information about households at the telephone-exchange level (an exchange is identified by the first six digits of a ten-digit telephone number). We used these auxiliary data in "propensity" models to adjust the sampling weights for nonresponse.

The results of our analysis in that study indicated that aggregate demographics from the Genesys file showed promise for adjusting RDD sampling weights; the response model was strongest of three models based on most tests. All models were somewhat weaker than experienced in some other applications where the propensity models were based on un-aggregated prediction variables. The significant variables in the resolvability model were education, home ownership, income, race and age; demographics such as education, income and telephone listings per "working hundred block" were important in the screening model; while income, age, race and number of listings in working hundred blocks were used in the response model.

A Comparison Of Two Methods To Adjust Weights For Non-Response: Propensity Modeling And Weighting Class Adjustments

A common method used to adjust sampling weights for non-response involves forming weighting classes of homogeneous sample members. Within each cell, the weights of the respondents are inflated to account for the non-respondents. Some problems inherent in this method are cells with too few respondents, adjustment or inflation factors that are too high, and potentially large differences in these adjustment factors from one cell to the next. While there are ways to deal with some of these problems, they generally involve the risk of increasing the mean square error, either through bias or in the variance of the weights. A relatively new approach involves developing logistic regression models to predict response, using a potentially much broader set of predictive variables than can be used directly or in the weighting class methodology. That is, the inverse of the response propensity resulting from the application of such a model can be used as the adjustment factor to the weights. We applied both of these methods when computing weights for round two of the Community Tracking Study (CTS) Household Survey (Carlson and Williams 2001). This study provides important background for the present study, because they both deal with the CTS Household surveys.

This earlier paper explored the differences resulting from these two methods. We found very little difference between the propensity method and the weighting cell method when looking at the CTS household survey RDD re-interview sample (a substantial portion of the sample consists of households interviewed in the prior round of this longitudinal survey). The expected benefits of the propensity modeling (less variation in the weights and less bias) were not seen. This is likely due to two main reasons: (1) the number of weighting cells here was so large (over 300) that the weighting cell approach nearly approximated the smoother nature of the propensity modeling approach, and (2) the screener and interview response rates among the household survey re-interview sample was high to start with, allowing for very little variation in the non-response adjustments.

Although the results were almost identical for weighting classes and propensity models, it is interesting to note that a parsimonious model containing a dozen or so carefully identified variables could produce essentially the same results as weighting class adjustments using hundreds of weighting classes based only on design features (strata and sampling units).

The results are survey specific; they cannot be expected to represent other surveys or other survey designs. For the analyses involving the entire round-two sample (not just the re-interview cases), it should be kept in mind that the "propensity model" is a hybrid approach, where the impact of the propensity model is diluted with the weighting cell approach used for the non-re-interview cases. The fact that the proportions of unresolved numbers and non-respondents are much greater in the non-re-interview group that used only weighting class adjustments lead us to suspect that the model adjustments do not have much opportunity to have an overall impact

Compensating for Provider Nonresponse Using Response Propensities to Form Adjustment Cells: the National Immunization Survey

This application we mention only briefly as an example of the varied uses of propensity models when compared to the above studies, in this case to form weighting classes (DHHS 2001). The use of logistic propensity models simply to identify variables for use in weighting classes is common, this particular application presents a slightly different application in that the estimated propensities are themselves used to form weighting classes, not just to identify variables for forming classes. Also, while it is a recent example of using propensity models to adjust for nonresponse, it only deals with the mail component of a mixed mode survey (not directly related to the RDD telephone component of the survey). A national model for predicting the probability that a sampled child has provider-reported vaccination history is used (basically this is a predictor of provider nonresponse based on household characteristics). The individual records are sorted according to value of predicted probabilities within each of 78 geographic-based strata. From 1 to 3 weighting classes were formed within each stratum, based on the frequencies of these predicted values in the stratum. The RDD weights for respondents within each of these classes were then adjusted to the total sample weights in the class.

2. Study Methodology

The Setting

The setting for our current study is the third round of the **CTS Household Surveys** – The Community Tracking Study (CTS) is a national study of the rapidly changing health care market and the effects of these changes on people. Funded by the Robert Wood Johnson Foundation, the study is conducted by the Center for Studying Health System Change. (Information about other aspects of the CTS is available at **www.hschange.com.**) Mathematica Policy Research, Inc. is the primary contractor for the household survey component. The third round of the household survey, the basis for the current paper, was completed in September 2001.

Genesys Sampling Systems was used to generate RDD numbers for this survey. As described above, *hundred-blocks* containing one or more listed telephone numbers were used to generate candidate telephone numbers. Also noted in general discussion of this method, three issues are often of concern: (1) some numbers cannot be resolved as to whether or not they are assigned to a household (assuming our survey is a household survey); (2) for those identified as households, the screening cannot be completed for some; (3) and for the screened households, some do not complete the interview. In the CTS household surveys, however, once the candidate number has been determined to be a working household number and the screening of the household is complete, essentially all of those screened completed the interview. Therefore, we limit this investigation to two models, number resolution and interviewing, rather than the three investigated in the previous study involving the single state.

The sample in the first round of the CTS Household survey (1996-97) consisted of two independently drawn random-digit dial (RDD) national samples (one clustered within 60 randomly selected sites and one un-clustered), and a small in-person component selected within 12 of the 60 sites. For the RDD sample in the second round (1998-99) and third round (2000-2001), we selected a relatively high percentage of telephone numbers that were associated with previous round completed interviews, a smaller percentage of telephone numbers that were associated with previous round sample members not resulting in completes, and then a sample of new numbers (telephone numbers that existed in the previous round but which were not selected and those that did not exist in the previous round).

Table 1 shows the response experience of the telephone numbers released in the RDD component of the Round 3 surveys. The selected sites are from the Site Sample, which is the clustered sample of 60 sites, and the Supplemental Sample is the smaller un-clustered survey component. Overall, the un-weighted household-level response rate for the RDD component was 63.7 percent (product of resolve and response rates). Specifically, we investigate the feasibility of using Genesys information to develop propensity models for resolvability of the RDD numbers and for the successful completion of the household interviews. The study is further limited to the national Supplement survey of Round 3 and selected sites in the Round 3 Site Survey.

Genesys

The information available to us in the Genesys sample files includes demographic characteristics at the telephone exchange level, such as age, income, race, education, and home ownership. Each exchange contains 10,000 potential telephone numbers. Many of these numbers are not assigned to households and the area covered by an exchange is large, diverse, and non-dense. This type of information is not ideal for developing propensity models, but is worth considering because of its availability and the lack of comparable person level data. We initially explored the merit of using such information to adjust for missing information on a small scale (*2002 study*—the first background study described above). In the present paper, we test the conclusions of that earlier study on other surveys with more complex designs (the CTS surveys). And in the second background study mentioned above, models were developed for the CTS surveys but only for the re-interview part of the sample and using prior round information—not the Genesys information.

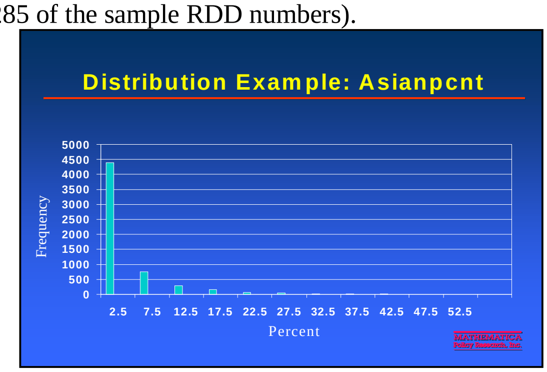
That is, we now investigate the feasibility of using auxiliary demographic information available on the Genesys sample files to predict RDD number "resolvability" and interview completion, the two major sources of sample attrition in the CTS household surveys. The results of the survey and the Genesys data will be the basis for constructing these two models. In addition to the Genesys data, geographic stratification and the field outcome codes also could be used as candidate independent (explanatory) variables. However, unlike in the 2002 study, we do not include these data in order to investigate the effectiveness of the Genesys information alone—more generalizable to the class of cross-sectional RDD surveys in general. We seek to use these auxiliary data in "propensity" models to adjust the sampling weights, in order to reduce the potential for bias that can result from the missing information.

3. Methodology

Propensity modeling -- We use propensity models, which are an increasingly popular method for adjusting for non-response: that is, creating a logistic regression model that predicts the likelihood of response versus non-response. Two propensity models were considered in each survey setting. For example for the National Supplemental sample: (1) a resolvability model for all 6,051 RDD numbers, to predict the likelihood of resolving the number as a household or non-household; and (2) a response model for the known households (3,703 records in our survey) to predict the likelihood whether or not the household will complete the interview. Of the 6,051 RDD numbers, 3,703 were households, 1702 were not household numbers, and 646 were unresolved. Of the 3,703 households, 28 were ineligible for the study, but 1,064 eligible households did not complete the survey. The unresolved numbers and the nonresponding households are the sources of missing information bias that the models are designed to address.

Constructing covariates for the propensity models The variables available for each RDD number in the Genesys sample files were a few dozen demographic characteristics at the telephone exchange level in which the telephone number resided, and one variable at the working bank level which was household listings per working hundred block. They are mostly continuous variables, such as the median household income in each exchange area. Continuous variables in the models, however, use only the linear relationship (unless higher-order terms are used). So if we simply used the Genesys variables as supplied, this would only allow us to capture linear relationships. We therefore decided to transform most of the continuous variables into a set of binary variables in order to capture nonlinearity.

First we partitioned each Genesys variable into approximately three or four ranges based on apparent break points in its frequency distribution. This is a simplification from the grouping of deciles based on response rates that was used in the 2002 study, seeking methodology that may lose some information but could be more feasible to implement. Using the above rule, two binary variables can be created for the percent of population that is Asian in the National Supplement sample. While the distribution of this example variable is very skewed and somewhat atypical, it demonstrates the approach:
The base (reference group) is the group of 0 to 4.9 % near (in this case containing) the average frequency, X1 = 5 to 14.9 (medium) and X2 = 15+ (high, with 285 of the sample RDD numbers).

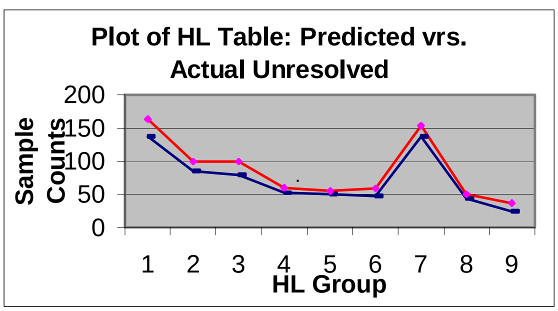


After creating binary variables for most of the continuous variables, we had approximately 85 candidate covariates for the models. Interactions were also investigated. Initially, Chi-square Automatic Interaction Detection (CHAID) program was used for investigating second- and third-order interactions of the approximately 85 variables. Following that, stepwise logistic regressions (forward and backward elimination) were run both with and without the interactions identified in CHAID. Little was gained by using the CHAID interactions compared to simply using the SAS logistic programs for main effects and second-order interactions, so this step was not used in the final runs. Also, in the initial runs, the data were weighted with sampling weights (scaled down to sum to sample size) for the SAS logistic solutions.

Two sets of tables were run: 1) using the dichotomy of whether or not the RDD number is determined to be a household and 2) the dichotomy of households that were interviewed or not interviewed. The chi-square p-values for the regression coefficients were used to reduce the number of variables and to identify a manageable number of candidates for interaction variables. In the 2002 study this step actually told about the same story as observing a summary of response rates by group except the regression analyses also present statistical significance.

Using weighted stepwise logistic regression in SAS -- Once the initial candidate variables for the two models were identified, we used stepwise weighted logistic regression (SAS Logistic) to reduce the list of variables in the two models before we considered possible interactions. Both forward and backward solutions for stepwise logistic regression in SAS were used, setting the significance level at 0.05. Somewhat different sets of variables are identified in the two different solutions. Part of the problem with forward solution is that once a variable is admitted, it is retained even though it becomes insignificant as a result of other variables or interactions entered into the model.

Sampling weights, adjusted at each stage, were used to obtain unbiased estimates. That is, we started with the resolvability model using the unadjusted basic sampling weights, which were the inverse probabilities of selection. The statistics assessing model fit and predictive ability of the model were output. At this point we identified a problem. Hosmer-Lemeshow (HL) statistic evaluates model fit. The HL statistic had a p-value of approximately 0.001, which indicates a terrible fit. The predicted and actual outcomes of groups used to obtain the HL statistic are summarized for approximately ten groups. The predicted values in this survey were all too high for the estimated number of unresolved cases. This indicates an upward bias, but our models are based on asymptotically unbiased maximum likelihood estimators.



We need to consider, however, what the unbiasedness relates to. Since we used sampling weights to estimate the model coefficients, the results will be unbiased for the population and proportional samples of the population. But our sample is not proportional because of oversampling of prior round respondents—the resolvable rate and response rates will be better than for a proportional sample. Hence, what we really need is a model that is effective for estimating the *conditional* probabilities of the second and third stages.

To explain, we note that to obtain an interview for a given household, three events must occur:

A. the household's number is in the sample,
B. the telephone number is resolved as being a valid household number, and finally,
C. the household completes the interview.

The joint probability of these events is:
P(ABC)=P(A)*P(B|A)*P(C|AB).

P(A) is known, determined by the design, but we must estimate the two conditional probabilities. Hence, we need a model that produces valid estimates for our particular sample, not for the population (this is indicated by the above chart of the weighted model results). Unweighted regression analysis of the sample of RDD numbers produces such a model for resolvability. Likewise, we must use unweighted analyses to estimate the last conditional probability relating to nonresponse. The resulting analyses weights are, therefore, based on an estimate of the joint inclusion probability, that is, the product of a constant and two asymptotically unbiased estimates of the conditional probabilities. Note that the weights based on this joint inclusion probability account not only for the disproportionate sampling of prior round respondents, but also the estimated response propensities. When going from the weighted model solutions to unweighted models, the HL statistic increased to the level of good models and all other statistics for predictive ability and model fit improved. Note, however, we cannot claim an unbiased estimate of the joint inclusion probability because of the potential correlation between the two conditional probability estimates.

Initially, the resolve and response models for the National Supplement were run with a significance level of 0.3. At that level, the stepwise logistic regressions reduced the list of variables (including interaction terms) to 35 for the resolvability model and 33 for the response model. Many of the main effects are included, even though not significant, because an interaction with the main effect is significant at that level. Table 2 presents the variables in these models to demonstrate the nature of the variables investigated, even though one might prefer a more parsimonious model limited to more significant variables. Reducing the significance level to 0.10 reduced the number of variables to 15 and 26 for the resolve and response models, respectively. Little was lost in the goodness of fit as a result.

The variables most important to the resolve model included the number of household listings in the working hundred-block and population age and income. The variables most important to the response model included the population counts, age, and income.

Running the final models in SUDAAN -- The final stage will be to enter the reduced sets of variables into the weighted logistic procedure in SUDAAN, and calculate the final parameter estimates using the design features (primarily stratification and disproportionate sampling). We have not completed this step and expect little change in the conclusions. Since the designs being used in this survey were stratified random sample with disproportionate sampling (no clustering), the SAS and SUDAAN runs are expected, based on previous experience, to be essentially the same: the parameter estimates equivalent and slightly different p-values for the individual parameter estimates.

3. Results

Table 2 shows the variables that were retained in the two comprehensive models for the National Supplement sample, using a significance cutoff of 0.3. Twelve main effects and 23 interactions were retained in the resolvability model and 17 main effects and 16 interactions were retained in the response model. Table 3 shows some statistics we used to test the goodness of fit and predictive power of the models. The first one tests the global null hypotheses (Likelihood ratio statistics) that all the explanatory variables have coefficients of zero. We can see from the table that P-values are very small for both models in all 5 settings, so we reject the null hypothesis and conclude that at least one of the coefficients for explanatory variables in each model is not zero. Recall that the five sites referred to, for Round 3 of the CTS household survey, are the National Supplement sample and four of the sites in the Site sample of Round 3. The sites are varied in geographic location and population density as well as survey problems: Boston; Orange County CA; Miami; and Lansing MI. Note that the degrees of freedom in these tests are equal to the number of covariates retained. Note also that all of the site models have used a significance level cutoff of 0.05.

The next step tests model goodness of fit, using two statistics: Hosmer-Lemeshow (HL) test and Deviance. HL test is based on grouping predicted probabilities into approximately ten cells. Larger p-values for the HL statistic indicate better fit (we don't want to reject the null). We can see from the table that all models pass this test. The deviance compares the fitted model with a saturated model, and again, larger p-values indicating better fit. The resolve and response models are good fits according to the deviance test, with the models for Miami and Lansing being slightly weaker. The deviance statistic can be unreliable if there are many or continuous explanatory variables in the model, because too many covariate profiles allow small cell counts, but this is not a problem for the models presented here (Allison 1999).

The last statistics describe how well we can predict the dependent variable based on the values of the independent variables. The model concordance shows that the models are effective, with the Orange County and Miami response models being the weakest. In other cases the spread between concordance and discordance is about 20 points or more, indicating relatively strong models. Three measures of association: Sommer's D, Gamma and Tau-a, can all range from zero to one, with larger values indicating better association between the predicted and observed values. These statistics are all based on the concordance/discordance numbers. Tau-a tends to be closest to the generalized R-square, which is a measure that is of limited use in the logistic setting and has much different meaning than the R-square we are familiar with in linear regression with continuous dependent variables. We see the association measures are relatively low. For predictive power, the response models appear to be slightly better than the resolvability models.

4. Conclusions and Limitations

The results indicate that aggregate demographics from the Genesys file are useful for adjusting RDD sampling weights. Although the test statistics vary, the resolve and response models appear very comparable. All models are somewhat weaker than experienced for propensity models based on un-aggregated data. The significant variables in the resolvability model were the number of household telephone listings per working hundred-block and population age and income. Population counts, income and age were in the response model. We recall that in the 2002 study, income, age, race and number of listings in working hundred blocks were used in the response model.

REFERENCES

Potter, F.J., McNeill, J.J., Williams, S.R. and Waitman, M.A., (1991) "List-Assisted RDD Telephone Surveys", Proceedings of the Section on Survey Research Methods, American Statistical Association, Alexandria, VA. pp 117-122.

Hosmer, D.W. and Lemeshow, S. (2000) Applied Logistic Regression 2nd Edition, John Wiley & Sons: New York

Allison, P. (1999) Logistic Regression Using the SAS System: Theory and Applications, SAS Institute, Inc., Cary, NC

Marketing Systems Group. Genesys Sampling Systems Methodology, Philadelphia, P.A. MSG 2000

Marketing Systems Group. Genesys Sampling Systems Methodology, Philadelphia, P.A. MSG 1994

Table 1: Response Experience in R3 of the CTS Household Surveys		
CTS Component	RDD numbers resolved (%)	Households Interviewed (%)
National Supplement	89.3	71.3
Boston	86.8	62.8
Orange County CA	84.3	60.2
Miami	84.6	57.3
Lansing	88.3	71.9

TABLE 2. LOGISTIC REGRESSION RESULTS FOR VARIABLES RETAINED IN PROPENSITY MODELS FOR THE NATIONAL SUPPLEMENT SURVEY

Resolve and Response Models										
Global Chi-Square Test (Likelihood Ratio)										
	National Supplement		**Boston**		**Orange County, CA**		**Miami**		**Lansing**	
	Resol.	**Resp.**	**Resol.**	**Resp.**	**Resol.**	**Resp.**	**Resol.**	**Resp.**	**Resol.**	**Resp.**
χ-Square	**164**	**125**	**66**	**47**	**90**	**32**	**119**	**26**	**46**	**40**
Degrees Freedom	**35**	**33**	**9**	**10**	**10**	**8**	**9**	**6**	**11**	**12**
P-Value	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**0.002**	**<0.001**	**<0.001**
Model Goodness of Fit (P-values for χ–square tests)										
H-L Test	**0.97**	**0.99**	**0.99**	**0.98**	**0.99**	**0.90**	**0.99**	**0.94**	**0.96**	**0.99**
Pearson	**0.74**	**0.55**	**0.79**	**0.81**	**0.48**	**0.82**	**0.33**	**0.24**	**0.42**	**0.51**
Statistics Measuring Predictive Power										
Concord.	**62.9**	**60.0**	**58.6**	**56.8**	**55.5**	**52.3**	**42.1**	**38.7**	**57.1**	**51.4**
Discord.	**34.8**	**37.8**	**32.2**	**36.8**	**30.5**	**35.5**	**18.8**	**26.1**	**35.3**	**31.0**
Somer's D	**0.28**	**0.22**	**0.26**	**0.20**	**0.25**	**0.17**	**0.23**	**0.12**	**0.22**	**0.20**
Gamma	**0.29**	**0.23**	**0.29**	**0.21**	**0.29**	**0.19**	**0.38**	**0.19**	**0.24**	**0.25**
Tau-a	**0.06**	**0.09**	**0.06**	**0.09**	**0.07**	**0.08**	**0.06**	**0.06**	**0.05**	**0.08**

TABLE 3. LOGISTIC REGRESSION RESULTS FOR SUMMARY STATISTICS OF RESOLVE AND RESPONSE MODELS IN FIVE SETTINGS

Resolvability Model		
Variable	**Coeffic.**	**P value**
INTERCEPT	1.753	<.0001
AGEONE3: high percent in ages 0-17	1.644	0.010
AGESIX1: low percent in ages 65-54	0.327	0.365
HHLST1: small number of listings in hundred block	-0.864	<.0001
HHLST3: large number of listings in hundred block	0.502	0.140
EDUYR1: small median years of education	0.142	0.554
HISP2: medium percent Hispanic	-0.046	0.791
INCONE1: small percent with income 1-10K	-0.082	0.573
INCFIV2: medium percent with income 35-50K	-0.111	0.562
INCSIX3: high percent with income 50-75K	0.240	0.559
MEDINC1: small median income	0.430	0.079
TTLHH2: medium number of households	0.302	0.073
TTLPOP1: small number of households	0.267	0.165
Interactions		
AGEONE3*HHLST1	-1.498	0.009
AGESIX1*HHLST1	0.274	0.233
AGESIX1*EDUYR1	-0.441	0.097
HHLST3*EDUYR1	-0.534	0.170
AGESIX1*HISP2	0.268	0.288
AGESIX1*INCONE1	-0.536	0.045
EDUYR1*INCONE1	1.008	0.201
EDUYR1*INCFIV2	0.543	0.019
AGESIX1*INCSIX3	0.446	0.275
HISP2*INCSIX3	0.500	0.170
INCFIV2*INCSIX3	-0.541	0.145
AGEONE3*MEDINC1	-1.321	0.010
HHLST1*MEDINC1	0.280	0.129
EDUYR1*MEDINC1	-0.407	0.077
HISP2*MEDINC1	-0.423	0.055
INCFIV2*MEDINC1	0.213	0.298
AGEONE3*TTLHH2	0.645	0.210
AGESIX1*TTLHH2	-0.338	0.273
HHLST1*TTLHH2	0.259	0.196
HHLST3*TTLHH2	0.714	0.086
AGESIX1*TTLPOP1	-0.363	0.274
INCONE1*TTLPOP1	-0.270	0.180
TTLHH2*TTLPOP1	-0.483	0.173

Response Model		
Variable	**Coeffic.**	**P value**
INTERCEPT	0.657	0.001
AGEONE1: low percent in ages 0-17	-0.273	0.014
AGEONE3: high percent in ages 0-17	0.089	0.760
AGEFOR1: low percent in ages 35-55	0.099	0.328
AGEFOR3: high percent in ages 35-44	0.352	0.194
AGESIX1: low percent in ages 65-54	0.311	0.014
AGESEVN1: low percent in ages 65+	-1.060	0.006
BLACK3: high percent in black population	0.483	0.046
INCTHR1 low percent with income 15-25K	-0.087	0.654
INCFOR1 low percent with income 25-35K	-0.144	0.565
INCFOR2 medium percent with income 25-35K	0.018	0.913
INCSIX1: low percent with income 50-75K	0.180	0.114
MEDRNT3: high median rent	-0.383	0.023
OWNOCCP3 high percent of owner occupied housing	0.434	0.005
TTLHH1: low number of total households	1.458	0.019
TTLHH2: medium number of total households	0.306	0.011
TTLPOP1: low number of total households	2.606	0.011
WHTPNT1: low percent white population	-0.391	0.035
Interactions		
AGEFOR3*AGESIX1	-0.539	0.124
AGEONE3*AGESEVN1	0.815	0.083
AGEFOR3*AGESEVN1	0.572	0.168
AGESIX1*AGESEVN1	0.541	0.167
AGEFOR3*INCTHR1	-0.566	0.265
AGESIX1*INCTHR1	-1.150	0.013
AGESEVN1*INCTHR1	0.776	0.046
AGEONE1*INCFOR1	0.594	0.007
AGESIX1*INCFOR1	0.795	0.062
INCSIX1*MEDRNT3	-0.710	0.014
INCFOR2*OWNOCCP3	-0.480	0.016
TTLHH1*TTLPOP1	-4.018	0.001
TTLHH1*WHTPNT1	-1.709	0.040
TTLPOP1*WHTPNT1	2.683	0.004
AGEFOR3*INCFOR1	0.436	0.387
OWNOCCP3*NCSIZ1	0.366	0.042