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LOGISTIC REGRESSION ANALYSIS OF CPS OVERLAP SURVEY SPLIT PANEL
DATA

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The complex nature of survey data changes the distributions of statistics associated with logistic regression models.  The variances in the traditional logistic regression models are generally too small, leading to overly liberal tests.  Roberts, Rao, Kumar (1987) provide a method for constructing approximate tests when a separate estimator for the covariance matrix is available. I apply this method with some modifications and the variance estimator described in Fisher et al (1993) to the CPS Survey split panel data.

I.      Introduction

The Census Bureau undertook an investigation (Thompson (1994)) into the effects of some changes in interviewing methods on Labor Force (LF) estimates.  A part of the study was focused on whether there is an effect on LF estimates from the use of personal computers during interviewing by telephone (CATI) vs. traditional interviewing, in person on paper (PAPI).  We will refer to this as a combined centralization and automation effect.  In this paper I apply a logistic regression analysis to get more information about the combined centralization and automation effect.  I was also interested in gaining understanding of the performance of this technique with CPS and related data.  In that context, this paper should be viewed as a first step in an attempt to implement logistic regression techniques in these analyses.  This approach is in contrast to that of  Thompson (1994), where the effect was tested separately in each of several subgroups.

The problem with the usual logistic regression is that the complex nature of the survey means the distributions of the estimators of the parameters is different than we would expect.  The variances and p-values in the traditional logistic regression are generally too small.  One possibility is to expand the model to explicitly incorporate the features of the complex sample design.  This approach can be daunting in the face of a design as complicated as CPS.  An alternative is to separately estimate the variation of pertinent statistics and incorporate that knowledge into the testing procedure.  Two notable approaches are the bootstrap and related methods, where the test statistic may be replicated with a jackknife or bootstrap (see, e.g. Fay (1985)), and methods which use

completely separate estimates of variance to adjust the test statistics or get approximations for the sampling distributions. Rao and Scott (1981, 1984) and Bedrick (1983) provide examples of the latter method for getting approximate tests in contingency tables. Different statistics are given depending on whether the whole covariance matrix for cell probabilities can be consistently estimated or just the variances. When only variance estimators are available, they give simple "first-order" adjustments to the Pearson chi-squared test statistic ($X^2$) and the likelihood ratio statistic ($G^2$). When an estimator for the whole covariance matrix is available, they gave adjustments to these statistics based on the Satterthwaite approximation to a weighted sum of $X^2$ random variables as well as a Wald statistic. They apply these tests to the Canadian Health Survey. Thomas and Rao (1987) and Thomas, Singh, and Roberts (1991?) showed the Wald statistic can be unstable when the number of cells is large and the number of sample clusters is small. Fay's jackknifed tests and the Rao-Scott connections performed well, however.

Roberts, Rao, and Kumar (1987) (RRK) assume a logistic regression model for cell proportions and provide corrections to the $X^2$ and $G^2$ goodness of fit statistics analogous to the Rao-Scott adjustments described above, a Wald statistic, and an F statistic. They further give the statistics for testing nested hypotheses. Rao, Kumar, and Roberts (1989) extend the results, giving weighted least squares estimators for generalized linear models with singular covariance matrices along with a Wald statistic. Nguyen and Alexander (1989) consider tests of independence of hierarchial log-linear models when cell and marginal design effects are fixed. Upton (1991) discusses exploratory data analysis for survey data using log-linear models. Graubard and Korn (1991) present another approach using BRR. Choi and McHugh (1989) use modifications to a chi-squared statistic based on modeling and estimation of correlations in each stage of multi-stage surveys. Shimizu and Choi (1992) and Choi (1992) apply the technique to particular survey applications. Thomas, Singh, and Roberts (1991) consider the power of tests for RxC tables for two-stage cluster sampling.

There have been some efforts to compare different approaches. Thomas, Singh, and Roberts (1991?) present a Monte Carlo study to compare the approaches of Rao-Scott (1981 and 1984) and Fay (1985) for small samples. Parsons (1992) compares some of the common approaches on surveys of the National Center for Health Statistics, including various simplifications of the design structure used in the derivations of test statistics. The most extreme example is to assume simple random sample variances. Carlson, Cohen, and Monheit (1992) explore alternative pieces of software on the basis of computational considerations. Their study includes SUDAAN, RTILOGIT, SAS PROC LOGIT, and SURREGR.     SUDAAN (eg. Shah (1989)) in particular is computationally expensive.

Section II gives some background about the split panel study as it relates to this paper. In Section III I describe the use of GVFs and a simple modelling of the  covariance

matrix for the logistic regression model of RRK. Section IV describes the results. Finally I conclude in Section V.


II.     Background

Sample Design

The CPS is a monthly survey of 60,000 eligible households. These households are selected to represent the population of the Nation and of each State. The probability sample of housing units is drawn using a multistage stratification procedure. The sampled households are located in 729 selected geographic areas. The largest metropolitan areas within each State are always included; the remaining areas of a State are sampled with probability of selection proportionate to the population of the area[1]. The sample is designed to provide a 1.8 percent monthly coefficient of variation[2] on the estimated national unemployment rate, assuming a 6 percent rate. It was also designed to meet specific reliability criteria for the monthly estimates of unemployment for 11 States; the remaining 40 have fixed levels of reliability for an annual average. At the national level, this means that a month-to-month change of 0.2 percentage point in the estimated unemployment rate is significant at a 90-percent confidence level.

Data Collection Design

In an effort to balance respondent burden with improved estimates of change, households are interviewed for 4 consecutive months, not interviewed for the next 8 consecutive months, and then interviewed for another 4 consecutive months.
Each month, a new household panel of approximately one-eighth the total monthly sample size (60,000/8 = 7,500 households) is initiated, and the panel which received its eighth interview the previous month is dropped. Thus, each month, eight different panels are being interviewed for the 1st, 2nd,..., and 8th time. This rotating panel structure means that three-quarters of the sample in a given month is retained in the sample the next month, improving the estimates of month-to-month change. In the CPS, first and fifth month-in-sample households are interviewed through personal visits. For subsequent months, the majority of interviews are conducted by telephone.

Prior to January 1994, most of the CPS data were collected with a paper survey instrument and translated into computer readable form using FOSDIC[3] technology.

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[1] Following each decennial census, a new sample of areas is selected. The current sample is based on the 1980 census.

[2] The coefficient of variation of an estimate is defined as the standard error of the estimate divided by the estimate.

[3] Film Optical Sensing Device for Input to Computers.

Approximately 9 percent of the data was collected by interviewers working in two centralized facilities using computer-assisted telephone interviewing. Only households in a subset of the CPS sample areas were eligible for centralized computer-assisted telephone interviewing (CATI). These areas were purposely chosen based on operational considerations and were generally large metropolitan areas.

Centralized computer-assisted telephone interviewing had been used in the CPS since January 1989, when a centralized facility in Hagerstown, Maryland, was opened. In order to minimize any potential effects on published CPS estimates, the percent of sample cases interviewed from CATI was originally kept small. Over the 5-year time period, the percent of the CPS sample interviewed from CATI gradually increased to the 9 percent level used in the 1993 CPS[4].

From January 1991 through December 1992, the Bureau of the Census and the Bureau of Labor Statistics jointly conducted a special study in the CPS CATI-eligible areas to measure the effects of centralized telephone interviewing combined with computer-assisted interviewing on CPS data. Findings from this study showed that inclusion of CATI produced a 0.8 percentage point higher unemployment rate (Shoemaker, 1993). However, this difference could not be attributed to CATI alone. The paper-and-pencil questionnaire itself was not administered from a centralized location; rather, it was a computerized version, with modified wording of the lead-in question to the labor force section[5]. Thus, it was impossible to distinguish whether this difference was due to centralization, computer-assisted interviewing, or a slightly modified questionnaire.

Hypotheses and Experimental Design

This analysis is a contrast study. To study the effect of a possible "treatment," the CPS sample was randomly split into two "independent" groups (split panels). Each panel is statistically representative of the parent sample. The treatment is administered to respondents in one of the two split panels. The treatment is excluded from the other panel. The difference between the estimates from the two panels gives an estimated difference of the "treatment effect."

Panel definitions:

**CATI Panel**  Households in this type of panel are eligible for interview at one of the centralized telephone facilities. Not all households in the panel will be interviewed by CATI. To be interviewed by CATI, a respondent must

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[4]To accommodate the increased CATI sample, a second telephone facility was opened in Tucson, Arizona, in 1992.

[5]See Rothgeb (1994) for a more detailed discussion of the lead-in question and possible influences of computer-assisted interviewing and centralization.

have a telephone and speak English or Spanish. More important, during the personal visit interviews (usually MIS 1 and MIS 5) the household must agree to be interviewed in subsequent months by telephone. If not, the household's subsequent interviews will be completed by a field representative, either by personal visit or by telephone. Generally, if the household has not been interviewed from a centralized telephone facility by mid-week, then the interview is transferred to a field representative for interviewing.

**NonCATI**
**Panel**           All households in this type of panel are ineligible for CATI interviewing. Thus, even if a household meets all of the basic requirements for CATI, the interview will be completed by a field representative (decentralized interviewing only).

The Month in Sample (MIS) refers to the number of months that a housing unit has been in sample. This is usually the same as the number of interviews that a household has undergone. For example. MIS 1 refers to the first interview. MIS 1 and MIS 5 interviews are always conducted by personal visit.

The analysis here centers on the CATI effect.

1.    Description

Tests of these hypotheses are based on data from the CPS. The PAPI questionnaire was used by the CPS field representatives (decentralized interviewing). A computerized version of the *questionnaire* with a slightly modified wording of the lead-in labor force question was used by the CPS CATI interviewers (centralized and computer-assisted interviewing). The centralized telephone interviewing effect was combined with computer-assisted interviewing, because the old questionnaire did not have a computerized version outside of the CATI environment. This study was a continuation of the study presented in Shoemaker (1989 and 1993) with respect to data collection. In the Shoemaker (1989) study, data was collected from June 1985 until December 1988, but the portion which measured the effect of CATI on labor force estimates started in August 1986. In the Shoemaker (1993) study, data was included from 1991 and 1992. In the present study, data was collected from October 1992 until December 1993, as part of the CPS Overlap Study (Bureau of the Census (1994)).

2.    Experimental Design

The sample within the CPS CATI-eligible areas was randomly split into two representative panels: CATI-eligible (Panel A) or nonCATI (Panel B). The

number of households in Panel A each month increased over time. Thus, the composition of both panels changed on a monthly basis. The only areas included in this study were those that had sample in both Panel A and Panel B.

Note that these panel estimates were **not** nationally representative, because they used data from a non-random group of sample areas. The population covered by the CPS CATI-eligible sample areas was approximately 12 percent black and 11 percent Hispanic.

Data obtained from the first and fifth interviews were excluded from the panel estimates for testing this hypothesis. Estimated monthly sample sizes of persons 16+ and unemployed persons for each panel are presented below.

| CPS Panel | Persons 16+ | Unemployed persons |
| --- | --- | --- |
| CPS CATI Panel A | 14,580 | 730 |
| CPS NonCATI Panel B | 16,250 | 740 |

The data were collected every month from October 1992 to December 1993. The data from March 1993 were omitted from the study: a CATI facility was closed during the March interview week because of a blizzard. The estimates of cell proportions were formed from estimates of totals averaged over these 14 months.

3.     Limitations

The confounding caused by the mix of CATI and non-CATI interviews in the CATI Panel A estimates was also present in these tests. Additionally, the Panel A interviews which were not completed at a CATI facility were conducted with a slightly different wording of the lead-in labor force question.

III.     Methods

We have a five-dimensional table of probabilities defined by the four binary predictors, race, sex, ethnicity, and test status, and the binary response variable, unemployment status. These four variables are defined below. The cell probability of an unemployment status in a race-sex-ethnicity classification is the probability of that status given the race-sex-ethnicity classification. The estimated number of population individuals in the studied areas in a cell is the sum of the weights of the sample individuals in the cell, where the weights are a combination of the CPS base-weights and the probabilities of membership in the test or control panel. See Bureau of the Census (1994) for a discussion of the weighting for this study.

The model I used was a natural one where a cell is defined by the binary variables test, race, sex, ethnicity, which are defined below.

| Variable | Values | Meaning of Values |
|----------|--------|-------------------|
| Test | 1 | Test:  CATI eligible |
|  | -1 | Control:  Non-CATI eligible |
| Sex | 1 | Male |
|  | -1 | Female |
| Ethnicity | 1 | Hispanic |
|  | -1 | Not Hispanic |
| Race | 1 | Black |
|  | -1 | Not Black |

We are mostly interested in the variable 'test'; that is, whether CATI eligibility has an effect on measures of Labor Force, in this case proportion unemployed.  The analysis can focus on whether terms with 'test' in them need to be present.

The log-odds ratio for cell i is

$$\text{logit}(p_i) = \underline{X}_i^T ß \tag{1}$$

where $\underline{X}_i$ is the vector of the indicator variables for the cell i, i=(1,...,I).  Here $\underline{X}_i$ has dimension s.

The methods described by RRK are derived by finding the asymptotic distribution of $X^2$ and $G^2$ and using that to obtain an adjustment which makes them approximately chi-squared.  The simpler adjustment depends on the covariance matrix of the estimated cell probabilities only through its diagonals.  A more precise adjustment requires an estimator for the whole covariance matrix.  Another possibility, which also requires the whole covariance matrix, is to simulate the asymptotic distribution of $X^2$ and $G^2$.

In this analysis, I estimate the covariance matrix of the cell proportions with the Generalized Variance Function (GVF) methods described by Fisher, et al (1993).  The method had to be extended to estimate correlations between cells.  To get an estimator for the covariance matrix, I decomposed it by conditioning on the total.  Let $\underline{X}$ be the estimator for the vector of levels of a characteristic in a population.

$$\text{Var}(\underline{X}) = E(\text{var}(\underline{X} \mid \Sigma X_i)) + \text{var} (E(\underline{X} \mid \Sigma X_i)) \tag{2}$$

Now say

$$E(\text{var}(\underline{X} \mid \Sigma X_i)) = M$$

where M is the covariance matrix for a weighted multinomial random variable. If W is the average weight,

$$[M]_{ii} = \text{var}(X_i \mid \Sigma X_i) \approx DEW(\Sigma X_i)p_i(1-p_i) \text{ and}$$
$$[M]_{ij} = -DEW(\Sigma X_i)p_i p_j,$$

where $p_i$ is the fraction of the population represented by cell i and DE is an average design effect. Say the other term is

$$\text{var}(E(\underline{X} \mid \Sigma X_i)) = \underline{pp}' \text{ var}(\Sigma X_i).$$

That is, $E(\underline{X} \mid \Sigma X_i) = \underline{p}\Sigma X_i$, the multinomial expectation. Now the estimated correlation becomes

$$\text{cor}(X_i, X_j) = \frac{-DEW(\Sigma X_i)p_i p_j + p_i p_j \text{var}(\Sigma X_i)}{(DEW(\Sigma X_i)p_i(1-p_i) + p_i^2 \text{var}(\Sigma X_i))^{1/2}(DEW(\Sigma X_j)p_j(1-p_j) + p_j^2 \text{var}(\Sigma X_j))^{1/2}} \tag{3}$$

The covariance matrix of $\underline{X}$ was estimated with

$$\hat{c}ov($$

where ^{Install Equation Editor and double-click here to view equation.} and $[\text{cor}(\underline{X})]_{ij} = \text{cor}(X_i, X_j)$. Notice this covariance matrix is not typically nonsingular.

The variance for cell i is ^{Install Equation Editor and double-click here to view equation.} was calculated with a Generalized Variance Function (GVF) method. We can decompose total variance for cell i

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Here n is the sample size, *Install Equation Editor and double-click here to view equation.* and DEF is a design effect. Note our model here has sample size n and *Install Equation Editor and double-click here to view equation.* expressed as random variables. Also note the design effect is only applied to the variance of *Install Equation Editor and double-click here to view equation.* conditioned on *Install Equation Editor and double-click here to view equation.* . This portion corresponds to the variance expression we usually see for CPS, that is, a variance like a simple random sample. In this study, however, we use estimates where there has been no raking procedure to force various population estimates to match census estimates of population. The other term has been added to account for the extra variation. Now assume W = SI, the sampling interval in the survey where SI = N/E(n). Then *Install Equation Editor and double-click here to view equation.* can be written

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BRR estimates from 1987 were used to estimate DEF and *Install Equation Editor and double-click here to view equation.* . Further adjustments are needed to make the estimates applicable to the weighting and sample size in the split panel study. The final expression for the variance estimator for panel s in the split panel study is

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Here, *Install Equation Editor and double-click here to view equation.* is the 1987 estimate of population size, *Install Equation Editor and double-click here to view equation.* is the split-panel estimate of population size for *Install Equation Editor and double-click here to view equation.* , panel s and

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is the probability of including

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in panel s.

A variance for an estimator for a cell proportion, say Install Equation Editor and double-click here to view equation. is calculated with the well-known Taylor expansion expression,

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The last step depends on the relationship

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which is met, for example under simple random sampling without replacement.

I estimated the parameter vector ß with a pseudo-likelihood method, where Install Equation Editor and double-click here to view equation. is the solution to the equation

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where $X^T = (X_1, ..., X_I)$, D=diag Install Equation Editor and double-click here to view equation. ,

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is the weighted sum of the whole sample,

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is the weighted sum from the $i^{th}$ cell,

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are the estimated cell probabilities of

being unemployed in the model, and q is the vector of observed cell probabilities of unemployment.

RRK preserve the familiar forms of the test statistics by providing adjustments to the traditional $X^2$ and $G^2$ statistics. The simpler adjustment to these statistics are where

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Install Equation Editor and double-click here to view equation. is the average eigen value of

Install Equation Editor and double-click here to view equation. Where

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H is an Ix(I-s) matrix of rank I-s such that Install Equation Editor and double-click here to view equation.

and

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The matrix Install Equation Editor and double-click here to view equation. has been dubbed the "generalized design effect matrix." They point out that the adjustments should work well when the coefficient of variation of the Install Equation Editor and double-click here to view equation. is small. RRK give an improved adjustment, based on the well-known Satterthwaite approximation, where

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or

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These statistics are approximately chi-squared with (I-s)/Install Equation Editor and double-click here to view equation.
degrees of freedom.

Here,

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This adjustment takes the variation of the Install Equation Editor and double-click here to view equation. into
account.

Another alternative is to simulate chi-squared random variables from the asymptotic
distribution of Install Equation Editor and double-click here to view equation. and Install Equation Editor and double-click here to view equation. .
These statistics have the same as the distribution as

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where the Install Equation Editor and double-click here to view equation. 's are independent chi-squared
random variables if the asymptotic theory of RRK holds. We
can get many realizations of random variables from these
distributions and estimate p-values. The result is the exact
asymptotic p-value except for the variation in the simulation,
which we can make small by using a lot of replications. I
used 10,000, so my estimated p-values have standard deviation

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I calculated the test statistics $X_c^2$, $G_c^2$, $X_s^2$, and $G_s^2$, to test the goodness of fit of each model along with the p-values based on the approximate distributions, also given by RRK. I also provide the simulated p-values mentioned above. I also test some nested hypotheses, where the model is partitioned as

and the hypothesis under test is

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H:ß$_2$=0 conditioned on this model. The test statistics are RRK's $X^2(2|1)$, $G^2(2|1)$, with p-values associated with their approximations and simulated p-values.

IV.     Results

The first test I performed was for the model with every effect except for the four-way interaction and the test-ethnic-sex interaction. This model had the goodness-of-fit p-values in table 1.

Table 1

| Test Statistic | P-value |
|---|---|
| $X_c^2$ | .83 |
| $X_s^2$ | .83 |
| $G_c^2$ | .82 |
| $G_s^2$ | .82 |
| $X^2$(sim) | .83 |
| $G^2$(sim) | .82 |

The model fit. In my search to find models with fewer parameters to still fit the data, I tried two major reductions in the data. First, I tried the reduction where all terms containing the test term were eliminated and performed the test of the reduced model given the larger model was true. The goodness-of-fit p-values are in table 2.

Table 2

| Test Statistic | P-value |
|---|---|
| $X_c^2$ | .030 |
| $X_s^2$ | .030 |
| $G_c^2$ | .081 |
| $G_s^2$ | .082 |
| $X^2$(sim) | .033 |
| $G^2$(sim) | .085 |

which led me to reject the null hypothesis of the reduced model; apparently there is evidence that some test effect is non-zero.

The test of the model with no test terms given the model in test 1 also led me to reject the null hypothesis that the model in test 2 is sufficient.

The other model I tried was that with only main effects.  The p-values are given in table 3.

Table 3

| Test Statistic | P-value |
|:---:|:---:|
| $X_c^2$ | .97 |
| $X_s^2$ | .98 |
| $G_c^2$ | .97 |
| $G_s^2$ | .97 |
| $X^2(\text{sim})$ | .97 |
| $G^2(\text{sim})$ | .96 |

The model cannot be rejected at significance .10.  Indeed, it is the model I chose. Examinations of the normalized residuals revealed nothing pathological; there did not appear to be any outlying cells.

The tests of the main effects models vs. any of those available with these variables do not lead me to reject the hypothesis that the main effects model is sufficient.  Further, the test of each model with a main effect absent rejects the hypothesis of an adequate model.

Estimates of the coefficients for the main effects model are in table 4.

Table 4

| Parameter | Estimate | Standard Error |
|:---|:---:|:---:|
| Intercept | -2.52 | .035 |
| Test | -0.07 | .020 |
| Race | -0.40 | .026 |
| Ethnicity | -3.17 | .029 |
| Sex | 0.19 | .020 |

These results are mostly in accord with the previous studies mentioned.  The Bureau of the Census (1993) tested differences of unemployment rates separately in several categories.  The results of those tests are reprinted in table 5.

Table 5


EFFECT OF CENTRALIZED TELEPHONE AND COMPUTER-ASSISTED
INTERVIEWING


Unemployment Rate
(14 Month Average, 10/92 - 12/93 excluding 3/93)


|  | CPS CATI Panel C | CPS NonCATI Panel D | Difference C-D | P-value |
|---|---|---|---|---|
| Total | 7.55 | 6.54 | 1.00 | 0.00* |
| Men | 7.78 | 6.81 | 0.96 | 0.00* |
| Women | 7.28 | 6.24 | 1.04 | 0.00* |
| White | 6.64 | 5.57 | 1.07 | 0.00* |
| Men | 6.91 | 5.80 | 1.11 | 0.00* |
| Women | 6.32 | 5.30 | 1.03 | 0.00* |
| Black | 13.42 | 12.30 | 1.12 | 0.18 |
| Men | 14.10 | 13.90 | 0.20 | 0.76 |
| Women | 12.84 | 10.98 | 1.86 | 0.04* |

CPS CATI Panel C =       CPS sample that can be sent to CATI, but includes nonCATI
                         sample.  NonCATI sample interviewed with paper and
                         pencil (PAPI).

CPS NonCATI Panel D =     CPS sample that cannot be sent to CATI.  All sample
                         interviewed with paper and pencil (PAPI).


MIS 1 and MIS 5 not included in Panel C or Panel D.


*Differences significant at the 10% level.

The only group in which they failed to detect a CATI effect was in Blacks and Black Males.  The analyses were organized differently but are not in disagreement.


V.     Conclusion

We have detected effects on unemployment due to Race, Sex, Ethnic Group, and CATI status.  These results are similar to those in the Bureau's original investigation.  That analysis was not designed to detect interactions.

The test statistics seem well behaved in this study;  we might be encouraged to use similar methods on other related projects like other parts of the mode effects study (Bureau of the Census (1993)).

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