The Extent and Consequences of Attrition in the Women's Employment Study

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Abstract: We address potential concerns with the cumulative effects of attrition in the Women's Employment Survey. Even though response rates were around 90 % during each wave, we find that attrition in the WES is not entirely random. In particular, the respondents represent a small oversample of women who continued to receive cash welfare. Any biases induced by the non-random attrition, however, tend to be quantitatively small. We develop a set of weights for use with the WES to correct for any non-random attrition and apply them to a sample analysis. We conclude that some users may desire to use the weights as a precaution especially in descriptive analysis. However, weighting is unlikely to have any substantive effect on analyses using WES data.

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Sample Design

The Women's Employment Study (WES) began in Fall 1997 with a simple random sample selected with equal probability from an ordered list of eligible women (n=8875). To be eligible, women had to reside in the Michigan study county, receive cash assistance in February of 1997 and meet the following requirements:[2]

- Unmarried women with children
- US citizens
- between the ages of 18 and 54
- racial identity of white or African-American

To derive a representative sample of the metropolitan area and the population of these welfare cases, staff at the Institute for Social Research (ISR) Survey Research Center proportionally selected cases by zip code, race (white versus African-American) and age.

Once the sample was selected, letters of introduction were sent, including a toll-free telephone number for respondents to call to arrange an interview. ISR interviewers from the community conducted face-to-face interviews, primarily in the respondents' homes. Interviewers were instructed to complete the domestic violence and life event history sections of the survey only if complete confidentiality could be assured. The average interview time was approximately 61 minutes at wave 1. Interview time increased to about 86 minutes at wave 5, as additional questions were added to the survey instrument at each wave.

The first wave response rate of 86.2 percent is calculated by dividing the interviewed cases by the sample cases (753/874). Excluded nonsample cases (n=26) represent instances in which the sample person resided outside of the sample county, no housing unit existed at the address, or the sample person was institutionalized for the duration of that wave's data collection period.

[2] Non-citizens and other racial/ethnicity groups were not included in the sample frame because they comprise a very small proportion of the population in the study county.

The subsequent waves were fielded in Fall 1998, Fall 1999, Fall 2001 and Fall 2003; each survey period lasted about 4 to 5 months. Once a respondent had failed to respond during one wave, survey staff did not attempt to locate her for a subsequent interview. Women left the study for various reasons. Over the course of the study period, several respondents died, others were located but had moved more than 50 miles from the study area and hence could not be personally interviewed, and others could not be contacted.

Now that all five waves of WES data have been gathered, it is appropriate to address questions about whether sample biases arose over the study period because of attrition. A potential user of this data source may have several questions. Is the final WES sample representative of the February 1997 universe of county welfare recipients from which the first wave sample was selected? Should weights be used in analyses of WES data? This document addresses these and related questions.

Random vs. Non-Random Response

Table 1 outlines the response rates and resulting sample sizes across all five waves of the WES. The response rate at each wave was very high relative to the response rates achieved by similar studies of current and former welfare recipients, ranging from 86 to 93 percent. The difference between the total sample sizes at adjacent waves gives the number of attriters between those two waves. For example, at wave 2, 693 of the 753 wave one respondents were interviewed and 60 respondents were not interviewed. By the fifth wave, 536 or 61 percent of the original 875 respondents who were eligible for wave 1 were interviewed.

The raw number of non-responding individuals does not indicate whether attrition has a significant effect on data analysis. If attrition were entirely random, the responding samples at each wave would still comprise a random sample of the original universe. Therefore we focus the majority of our analysis on determining the extent to which attrition induces a non-random sampling frame. In this paper, however, we consider only the possibility that attrition is non-random with respect to characteristics measured in the data. Non-random attrition can potentially reflect selection on traits observable to the researcher (such as age or race) or traits that are not

measured in the data (for example motivation, general willingness to help, etc.). This paper examines and develops a method to correct for selection on observables by using observed characteristics to construct weights. While we find little evidence of selection on these observable traits, our analysis cannot rule out selection on unobservable traits.

Attrition on the basis of traits not in the data can bias regression results if the unobserved characteristics that affect attrition are also correlated with the unobserved characteristics that affect the dependent variable. For example, if attrition is correlated with unobserved motivation and if motivation is correlated with education then this will lead to bias in a wage regression with education as an explanatory variable since education is now correlaed with the error term in the regression. Testing or correcting for attrition on unobservables requires stronger assumptions than correcting for selection on observables. Users of the WES data, therefore, should be careful to consider the possibility of selection on unobservable factors and its potential effect on their analysis even though we find little evidence of selection on observables.

We employ two primary methods to address the question of whether non-random attrition based on observable characteristics induces a non-random sampling frame. First, we directly compare the WES sample at each wave to the entire population of interest (the February 1997 caseload of 8875 welfare recipients) using a small set of administrative data provided by the Michigan Family Independence Agency for everyone eligible for participation in the first wave, including all WES participants. If attrition were non-random, the means of these variables among the WES respondents and the means in the entire February 1997 population would start to diverge over time. Second, we attempt to predict wave-to-wave attrition using wave-specific data for study participants. Using this information, we can construct weights that correct for any non-random sample attrition related to variables we can observe. We then explore whether the use of these weights is likely to change the results of a typical WES analysis.

Comparisons Using Administrative Data

In most analyses of attrition, the investigators are limited by two obstacles. First, the target population is usually quite large so that collecting any data for every member is

prohibitively costly. In addition, in the standard case, once a respondent leaves the sample, no further information is collected about that individual. With the WES, however, we have the advantage that the Michigan Family Independence Agency (FIA) had collected and continued to collect program participation data on the entire universe of welfare participants eligible for the study[3]. The Agency has graciously provided those data to the research team at the University of Michigan's Program on Poverty and Social Welfare. Although these data cover only a small range of topics, we can use these data to help determine whether WES respondents at any wave are statistically significantly different from the population from which the study sample was drawn.

Table 2 gives descriptive information for the universe of February 1997 cash assistance recipients in the county and for each subsequent wave of WES participants. All variables are measured as of February 1997**,** unless otherwise noted. For example, the mean age of the 8875 welfare recipients who were eligible to participate in WES was 29.13 years in February 1997. Among those who participated in the first wave, the mean February 1997 wage was 29.39; among those who participated in the fifth wave, the mean age was 29.91. Similarly, 60.8 percent of the universe was listed in the administrative records as having a high school degree in February 1997; 60.0 percent of wave 5 respondents were reported as being high school graduates in February 1997.

Table 2 provides a sense of the magnitude of any differences between the WES sample and the population it represents. In order to ascertain whether these differences are significant, we performed a series of t-tests comparing the sample mean of a given variable with the population mean of the variable for the target county at each wave[4]. The results of this analysis

[3] The Agency has since changed its name to the Michigan Department of Human Services.

[4] Because all WES respondents also appear in the administrative data, this analysis compares the mean of a subsample to the mean of the population of all administrative data, including the WES subsample. This method introduces an error in the estimate of the difference. The estimate assumes that the groups measured are non-overlapping, so it assumes that there are really (8875 + 753) observations instead of only 8875 with 753 duplicates. Because the identification numbers have been scrambled, there is no way for us to create a comparison universe that deletes these duplicates. Estimates based on a larger data set will be more precise; therefore these difference estimates appear more precise than they really are. This means the bias will be toward finding differences. Nevertheless the differences we find are small; so this measurement issue, if anything, strengthens our claim that attrition bias in WES is small.

are presented in Tables 3 and 4. Table 3 examines all of the demographic variables provided to us in the state administrative records—race, age, high school degree completion, earnings in February 1997 and number of recipients in the case. We are unable to reject the hypothesis that the means are the same across waves for these five variables at most waves. We conducted 25 such t-tests, of which only five are significant.

The differences that are significant, however, appear to be the result of a pattern. Women who are slightly older and women who have slightly larger families are more likely to remain in WES than are other respondents. This result provides some evidence that attrition in the WES is not entirely random, although the differences between sample means and their corresponding population means induced by this non-random attrition are substantively small (less than one year in age, 29.91 v. 29.13 years, and around a quarter of a family member in size, 4.59 v. 4.34 persons).

In addition to these static demographic characteristics, we also have information on the program participation of the WES sample and the population over the sample time frame. Table 4 displays t-tests for the percentage of months that the FIA reported respondents were receiving a cash assistance payment in a given calendar year. As in the previous portion of the table, the null hypothesis is that the two means are equal. These t-tests do show significant differences, with 21 out of the 40 significant at the 10% level, and 11 of 40 significant at the 5% level.

These results imply that WES respondents received welfare for a somewhat greater number of months than did the universe. However, these differences, while statistically significant, are not substantively large. For example, among the universe of 8875, the average client received cash assistance during 78.2 percent of the months in calendar year 1997. The average wave 5 WES respondent, received welfare in 81.5 percent of the months in 1997. In calendar year 2004, the 8875 women received welfare for 19.19 percent of the months, while the 536 wave 5 respondents received welfare for 22.09 percent of the months.

For a complete picture, consider Figure 1 which plots the monthly welfare usage over time by women in the WES sample and women in the original sampling population. Although

there are statistically significant differences in usage month by month, the overall time pattern is qualitatively similar. The women in the WES sample experienced a dramatic decrease in cash assistance participation from February 1997 to late 2000 followed by a leveling off for the months through August 2004, as did the population as a whole. Although WES slightly oversamples women who received cash assistance, the sample participants' experiences with welfare over time are wholly consistent with the target population's.

These facts are consistent with the following interpretation. People can leave welfare for many reasons, including moving out of the state or moving to another area to take a job. Alternatively, they could leave welfare because they find employment, get married, or simply decide that getting welfare is not worth the hassle. Regardless of the reason for leaving, the welfare leavers would appear in the administrative database as no longer receiving cash welfare. However, when people leave the welfare rolls because they have left the study area entirely, they are not available for follow-up WES interviews. Thus, the WES interviewers are able to contact only a portion of the welfare leavers, while in principle it would be possible to contact all welfare stayers. This discrepancy could be responsible for the slight oversampling of welfare stayers in subsequent waves.

An alternative interpretation is consistent with reports from the ISR interviewers. They reported that they had a harder time setting up a 90 minute home interview with respondents who were employed. These working mothers obviously had less time at home, and the small interview incentive fee ($30 each wave) was likely less valuable for working women. Because employed women are more likely to leave the welfare rolls, this explanation also likely contributes to the slight undersampling of welfare leavers.

Constructing Sample Weights to Correct for Non-Random Attrition

The previous section suggests that attrition in the WES does not severely handicap the survey's representativeness. One alternative would be simply to conclude that attrition is not a severe problem and to suggest that users ignore attrition in their analysis.

An alternative is to provide potential users with a set of weights that correct the WES data for any non-randomness in attrition. In constructing these weights, we largely follow the model laid out in Fitzgerald, Gottschalk, and Moffitt (1998).

We create propensity score weights for each individual in each wave. Propensity score weights are inversely proportional to the predicted probability that a woman remains in the sample, based on her observable characteristics. By structuring the weights in this way, we give a greater weight to individuals who, based on the previous wave's information, were less likely to remain in the sample. Suppose for example, that there were only one variable, "employment at wave *t-1*," and that the employed were more likely to attrite than the unemployed. Then in wave *t* the employed respondents who remain in the sample should be weighted more heavily than respondents who are not employed. Each wave *t* respondent who was employed in the previous period represents a greater share of the target population than does a wave *t* respondent who was not employed. In this simple example, the propensity score weight would be defined as

$$\frac{1}{\hat{P}(Observed_t \mid Emp_{t-1} \mid)}$$

Here $\hat{P}(Observed_t \mid Emp_{t-1} \mid)$ stands for the probability that a survey participant responds in wave *t* given her employment status in the previous wave. The hat over the *P* serves as a reminder that this number is calculated from the sample data. Women who had been employed in the previous wave would be given a greater weight in the subsequent period because they were less likely to be observed in the subsequent period.

There are, in fact, several variables in the WES that could predict the likelihood of response in the following wave, but the intuition in the multivariate case is much the same as this one variable example. We now turn the derivation of the propensity score weights.

Methodology

We first estimate the following probit model for each of the second through fifth waves:

$$R_{it} = X_{it-1}\beta + \varepsilon$$

R_{it} is a dummy variable denoting whether individual *i* responded to the survey in wave *t.* X_{it-1} is a vector of characteristics specific to the individual in the previous wave, and ε is an error term modeled as a standard normal variable. We included a large number of variables from the survey that cover a wide range of human capital, physical health, mental health (the "standard WES employment barriers") and demographic factors as regressors. The results of this estimation for waves 2 through 5 are displayed in Appendix Tables 1.2-1.5.

The coefficient estimates support our previous discussion. Attrition in the WES appears to be primarily random (at least with respect to observable characteristics), as only a handful of variables in each regression statistically significantly predict a successful follow-up interview in the next wave. Consistent with previous findings, these estimates sometimes suggest that older women and women who are receiving welfare later in the sample period are more likely to remain in the sample. There is, however, no variable that consistently (across all waves) and statistically significantly predicts response in the following period. This lack of consistency suggests that using the weights will likely have very little effect on measured outcomes, an issue to which we will return later in this paper.

Once we have estimated the probit regression model, we use the parameter estimates to create an individual-specific predicted probability of response in the current wave $\hat{R}_{it}$ [5]. This predicted value tells us the likelihood that a wave *t-1* respondent with characteristics X_{it-1} was interviewed at wave *t*.

For each responding individual in a given wave, we then generate a cumulative predicted probability $\hat{P}_{it}$ that the individual remained in the WES analysis at least through the current wave. We simply use the product of the $\hat{R}_{it}$'s up to and including the current wave. For example, in wave 4, a respondent's predicted probability is:[6]

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[5] Note that these predicted probabilities are conditional on remaining in the sample through wave *t-1.* After an individual has left the sample, she is not contacted again. Thus, the probability of being in the sample in wave *t* for a wave *t-1* attriter is zero. These individuals are not included in the estimation of the probit models and thus do not receive predicted values or weights in waves following their attrition.

[6] We have implicitly assumed that only variables measured at *t-1* affect attrition between waves *t-1*and *t*. In other words, the only way factors occurring prior to wave *t-1* can affect the probability of being in the sample in wave *t* is

$$\hat{P}_{i4} = \hat{R}_{i2} * \hat{R}_{i3} * \hat{R}_{i4}$$

The weight assigned to each individual is then[7]

$$w_{it} = 1/\hat{P}_{it}$$

This weighting scheme achieves the objective of giving higher weights to individuals who were less likely to remain in the sample and lower weights to women more likely to be successfully interviewed.

A note on missing values: missing values on the various characteristics used as regressors provide a difficult problem for the estimation of these weights. Namely, if a respondent who was interviewed has a missing value for some variable, then as usual, that observation does not contribute to the regression, reducing its degrees of freedom. In addition, and more important for the present purpose, no propensity score can be assigned to that observation, and therefore no weight can be assigned.

We use two methods to address missing data. First, we avoid including those variables that are the least robust, that is, ones that have the most missing values. Then, for those observations which do have missing values, we impute a propensity score by replacing missing values with the mean value of that variable in the data set. Imputations have their own problems, so we stressed avoiding missing-valued variables so that imputation would be infrequent. These imputations were only used in the calculation of weights—the imputed values of the variables are not retained in the data or used in any of our tables. Using this method of imputation, we were able to create a weight for each individual in each wave, even if some information is missing.

Analysis of the Constructed Weights

Summary statistics for these weights are displayed in Table 5, and histograms showing the entire distributions are given in Appendix Figure 1. The rising means from wave to wave

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through their effect on attrition in prior waves. We made this assumption both for simplicity and because the sample size of the WES does not allow us to estimate late-wave attrition on the entire history of variables.

[7] For convenience, we also normalize the weights so that the weighted sample size remains 753 across time periods. This changes the weights only slightly, as the unadjusted totals range from 752 to 755.

reflect the lower sample size in each wave. In the same way that the raw response rates do not determine whether attrition is problematic, the rising mean does not imply anything problematic about attrition. Even if attrition were entirely random, the mean weight would be rising from wave to wave due to the fact that each $\hat{P}_{it}$ must be between zero and one, and thus an individual's weight must increase or remain the same from wave to wave.

Unfortunately, we are not aware of any statistical test that can use the set of weights we have created and determine whether attrition is problematic for this dataset. Instead, our recommendation is that users of the data run their analysis with and without the weights we have created to see if weighting makes any substantive difference in their conclusions. In most cases, however, choosing to weight should not make any noticeable difference, and we suggest this merely as a precaution. We would be genuinely surprised to find a research question for which the weighting decision made a substantive difference. In support of this claim, the next section presents some sample analyses, run both with and without weights.

Analysis with and without weights

Tables 6.2-6.5 report the weighted and unweighted summary statistics of a number of variables used in WES analyses for each of waves 2 through 5. There are very small differences between the weighted and unweighted means, and they are especially small when compared to the standard deviations. Notice, however, that the changes move in the direction we would expect. For example, the weighted sample is slightly younger (29.7 years v. 29.9 years at wave 2), and is less likely to have remained on welfare at any point in time (e.g. 26 v. 29 percent at wave 5) .

On the one hand, these differences demonstrate the power of the propensity score weights to correct for non-random attrition. On the other, the small magnitude of the differences between the weighted and unweighted results serves as a reminder that the majority of attrition can be considered unrelated to observable characteristics. Although the choice to weight descriptive statistics will likely have only small effects on the information conveyed, some users may prefer weighting to provide a potentially more accurate picture.

Whether a user should use weights in regression analysis is a more difficult question and depends on a number of different factors. A full treatment of the benefits and challenges inherent in weighted regression analysis is available in Deaton (1997). In addition to the standard challenges in weighted regressions, the propensity score weights we have developed to correct for attrition in the WES are estimated rather than based on known population parameters. If WES interviewers had intentionally allowed members of different demographic groups to leave the sample, we could have developed a set of weights based on errorless measures of attrition probabilities. Instead, the propensity score weights are imprecise and sample dependent. Considering this issue along with standard econometric arguments against weighting in regressions, we believe that most users will desire not to use weights in their regression analysis. In addition, the small dispersion of the weights suggests that even if WES users did choose to run weighted regressions, the results would not likely change in any significant way.

Despite these concerns, we have conducted a sample regression analysis that uses the the weights we have constructed. Table 7 is adapted from Jayakody, Danziger, Seefeldt and Cadena (2006), and details the difference in outcomes for women who got married after the beginning of the WES sample. Each column shows the results from a regression of the dependent variable on standard barriers variables and an indicator for whether the woman was married. The authors also include a measure of the length of the marriage. These regressions use individual level fixed-effects to account for unobserved time-consistent characteristics as well as wave dummies to control for common shocks across time. The goal of this analysis is to determine whether marriage (among those who chose to marry) helped or harmed women along a number of dimensions. These regressions include information from all five waves and thus take full advantage of the propensity score weights' ability to correct for non-random attrition based on observables. As in the descriptive analysis, there are no noticeable differences in the regression coefficients as a result of weighting. Again, we expect that other users will have similar experiences in their analyses.

Conclusion

The WES benefited from a very high response rate, and only about ten percent of the sample was lost between any two waves. Nevertheless, there is evidence that, in a small and inconsistent way, the attrition was related to observable characteristics of survey respondents. To correct for non-random attrition based on observables, we have developed a set of weights that can be used with WES analyses. We have not seen any evidence, however, that the use of these weights will alter the substantive conclusions of research using the WES data. Weights will be most useful to researchers when providing descriptive statistics. Using the weights in regression analysis usually will be unnecessary.

Cited References

Deaton, A. *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy, Washington D.C., The World Bank.*

Fitzgerald, J., Gottschalk, P., & Moffitt, R. (1998). An analysis of sample attrition in panel data. *The Journal of Human Resources, 33*(2), 251.

Additional Resources Used

Curry, Deb. "WES Attrition Report (#1)," Poverty Research Center internal document. October 2001. (Universe to waves 1, 3 comparison.)

Curry, Deb. "WES Attrition Analysis (#2)," Poverty Research Center internal document. January 2001.
(Universe to waves 1, 3 comparison.)

Nam, Yunju. "Attrition," Poverty Research Center internal document. February 2001.
(Waves 1 to 2, 1 to 3 comparison.)

Wang, Hui-Chen. "Sample Attrition," Poverty Research Center internal document. October 2000.
(Waves 1 to 3 hazard rate comparison.)

Table 1: Attrition from the WES Panel Study Data Set

	Response Rate	Sample Size	Total # not interviewed in wave	Cumulative Response Rate
Wave 1, Fall 1997	86%	753	122	86%
Wave 2, Fall 1998	92%	693	60	79%
Wave 3, Fall 1999	91%	632	61	72%
Wave 4, Fall 2001	91%	577	55	66%
Wave 5, Fall 2003	93%	536	41	61%

Table 2: Women's Employment Study: Universe to Waves 1 through 4 Comparison

Variable	Universe		Wave 1		Wave 2		Wave 3		Wave 4		Wave 5	
	N	%	N	%	N	%	N	%	N	%	N	%
Total Num Obs	8875		753		693		632		577		536	
Race												
Black	4803	54.1%	407	54.1%	369	53.2%	338	53.5%	308	53.4%	284	53.0%
Non-Black	4072	45.9%	346	45.9%	324	46.8%	294	46.5%	269	46.6%	252	47.0%
Age (Feb '97)	8875		751		692		631		576		535	
Mean		29.13		29.39		29.57		29.61		29.73		29.91
Median		27.88		28.01		28.30		28.41		28.60		28.77
Std. Dev.		7.37		7.42		7.50		7.47		7.50		7.59
% Months on Welfare												
1997	8875		753		693		632		577		536	
Mean		78.2%		81.4%		81.3%		81.2%		81.2%		81.5%
Std. Dev.		28.6%		25.9%		26.0%		26.1%		26.2%		26.0%
1998	8875		753		693		632		577		8875	
Mean		46.3%		49.2%		50.5%		50.2%		49.8%		49.8%
Std. Dev.		41.0%		40.4%		40.3%		40.3%		40.2%		40.1%
1999	8875		753		693		632		577		536	
Mean		31.0%		32.7%		33.6%		34.1%		33.7%		33.5%
Std. Dev.		38.8%		39.0%		39.2%		39.5%		39.3%		39.5%
2000	8875		753		693		632		577		536	
Mean		23.8%		24.5%		25.1%		26.6%		26.6%		26.7%
Std. Dev.		36.9%		37.4%		37.7%		38.6%		38.7%		38.8%
2001	8875		753		693		632		577		536	
Mean		21.0%		21.4%		22.5%		23.1%		22.9%		22.8%
Std. Dev.		36.0%		35.8%		36.4%		37.0%		37.0%		37.2%
2002	8875		753		693		632		577		536	
Mean		20.5%		22.3%		23.5%		23.9%		24.0%		24.4%
Std. Dev.		34.6%		35.6%		36.2%		36.7%		36.7%		37.0%
2003	8875		753		693		632		577		536	
Mean		19.5%		19.7%		20.9%		21.5%		21.9%		22.3%
Std. Dev.		35.2%		35.1%		35.8%		36.2%		36.6%		37.0%
2004	8875		753		693		632		577		536	
Mean		19.2%		19.1%		20.0%		20.5%		21.2%		22.1%
Std. Dev.		35.8%		36.2%		36.9%		37.2%		37.9%		38.5%
High School Completion (Constructed from FIA Employment code, Feb 1997)												
Yes	4482	60.8%	378	59.5%	347	59.5%	315	59.7%	289	60.2%	266	60.0%
No	2888	39.2%	257	40.5%	236	40.5%	213	40.3%	191	39.8%	177	40.0%
Missing	1505		118		110		104		97		93	
Earned Income (Feb '97)												
	8875		753		693		632		577		536	
Mean		160.42		163.96		165.04		166.57		168.57		173.78
Std. Dev.		264.45		267.86		267.30		268.45		267.29		272.61
# On Case	8875		753		693		632		577		536	
Mean		4.34		4.45		4.47		4.52		4.54		4.59
Median		4.00		4.00		4.00		4.00		4.00		4.00
Std. Dev.		2.34		2.44		2.46		2.50		2.56		2.58

Table 3: T-Test Results for Non-Welfare Variables

Variable	Class	N	Mean	Difference
Black v. Non-Black	Universe	8875	54.1%	
	WES wave 1	753	54.1%	-0.07%
				(1.9%)
	WES wave 2	693	53.3%	-0.87%
				(2.0%)
	WES wave 3	632	53.5%	-0.64%
				(2.1%)
	WES wave 4	577	53.4%	-0.74%
				(2.1%)
	WES wave 5	536	53.0%	-1.13%
				(2.2%)
Age in 1997	Universe	8875	29.13	
	WES wave 1	751	29.39	0.26
				(0.28)
	WES wave 2	692	29.57	0.44
				(0.29)
	WES wave 3	631	29.61	0.48
				(0.30)
	WES wave 4	576	29.73	0.60 *
				(0.32)
	WES wave 5	535	29.91	0.78 * *
				(0.33)
High School Diploma	Universe	7370	60.8%	
	WES wave 1	635	59.5%	-1.29%
				(2.0%)
	WES wave 2	583	59.5%	-1.29%
				(2.1%)
	WES wave 3	528	59.7%	-1.16%
				(2.2%)
	WES wave 4	480	60.2%	-0.61%
				(2.3%)
	WES wave 5	443	60.1%	-0.77%
				(2.4%)
Earned Income In 1997	Universe	8875	160.42	
	WES wave 1	753	163.96	3.54
				(10.05)
	WES wave 2	693	165.04	4.62
				(10.44)
	WES wave 3	632	166.57	6.15
				(10.90)
	WES wave 4	577	168.57	8.15
				(11.37)
	WES wave 5	536	173.78	13.36
				(11.78)
Number Recips On Case in 1997	Universe	8875	4.34	
	WES wave 1	753	4.45	0.11
				(0.09)
	WES wave 2	693	4.47	0.13
				(0.09)
	WES wave 3	632	4.52	0.18 *
				(0.10)
	WES wave 4	577	4.54	0.20 *
				(0.10)
	WES wave 5	536	4.59	0.25 * *
				(0.10)

Based on the overall and WES datasets. Numbers in parenthesis are standard errors.

Table 4: T-Test Results for Welfare Variables

Variable		N	Mean	Difference
% Mon on Welfare 1997	Universe	8875	78.20%	
	WES wave 1	753	81.41%	3.20% * * * (1.1%)
	WES wave 2	693	81.33%	3.10% * * * (1.1%)
	WES wave 3	632	81.17%	3.00% * * (1.2%)
	WES wave 4	577	81.17%	3.00% * * (1.2%)
	WES wave 5	536	81.50%	3.30% * * * (1.3%)
% Mon on Welfare 1998	Universe	8875	46.34%	
	WES wave 1	753	49.23%	2.90% * (1.6%)
	WES wave 2	693	50.48%	4.10% * * (1.6%)
	WES wave 3	632	50.17%	3.80% * * (1.7%)
	WES wave 4	577	49.75%	3.40% * (1.8%)
	WES wave 5	536	49.80%	3.50% * (1.8%)
% Mon on Welfare 1999	Universe	8875	30.98%	
	WES wave 1	753	32.70%	1.70% (1.5%)
	WES wave 2	693	33.59%	2.60% * (1.5%)
	WES wave 3	632	34.06%	3.10% * (1.6%)
	WES wave 4	577	33.67%	2.70% (1.7%)
	WES wave 5	536	33.49%	2.50% (1.7%)
% Mon on Welfare 2000	Universe	8875	23.80%	
	WES wave 1	753	24.46%	0.70% (1.4%)
	WES wave 2	693	25.10%	1.30% (1.5%)
	WES wave 3	632	26.61%	2.80% * (1.5%)
	WES wave 4	577	26.56%	2.80% * (1.6%)
	WES wave 5	536	26.74%	2.90% * (1.6%)

Table 4: T-Test Results for Welfare Variables (con't)

	Universe	8875	21.03%	
% Mon on Welfare 2001	WES wave 1	753	21.36%	0.30% (1.4%)
	WES wave 2	693	22.46%	1.40% (1.4%)
	WES wave 3	632	23.09%	2.10% (1.5%)
	WES wave 4	577	22.93%	1.90% (1.6%)
	WES wave 5	536	22.79%	1.80% (1.6%)
	Universe	8875	20.47%	
% Mon on Welfare 2002	WES wave 1	753	22.33%	1.90% (1.3%)
	WES wave 2	693	23.52%	3.10% * * (1.4%)
	WES wave 3	632	23.92%	3.40% * * (1.4%)
	WES wave 4	577	24.05%	3.60% * * (1.5%)
	WES wave 5	536	24.36%	3.90% * * (1.6%)
	Universe	8875	19.52%	
% Mon on Welfare 2003	WES wave 1	753	19.71%	0.20% (1.3%)
	WES wave 2	693	20.95%	1.40% (1.4%)
	WES wave 3	632	21.51%	2.00% (1.5%)
	WES wave 4	577	21.89%	2.40% (1.5%)
	WES wave 5	536	22.31%	2.80% * (1.6%)
	Universe	8875	19.19%	
% Mon on Welfare 2004	WES wave 1	753	19.07%	-0.12% (1.4%)
	WES wave 2	693	20.01%	0.80% (1.4%)
	WES wave 3	632	20.46%	1.30% (1.5%)
	WES wave 4	577	21.25%	2.10% (1.5%)
	WES wave 5	536	22.09%	2.90% * (1.6%)

Based on the overall and WES datasets. Numbers in parenthesis are standard errors.

Table 5 - Summary Statistics For Weights by Wave

	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
Wave 1	753	1	0	1	1
Wave 2	693	1.08658	0.1666645	0.9971339	4.094973
Wave 3	632	1.191456	0.1740168	1.002842	2.291256
Wave 4	577	1.305026	0.2259985	1.005393	2.614391
Wave 5	536	1.404851	0.2926559	1.005281	2.800345

Table 6.2
Wave 2 Summary Statistics - Weighted and Unweighted

	No Weights		With Weights	
	MEAN	STD	MEAN	STD
Age	29.94	7.46	29.71	7.41
Race (1=Black)	0.55	0.50	0.56	0.50
Alcohol Dependence	0.01	0.11	0.01	0.11
Major Depression Disorder	0.17	0.37	0.16	0.37
Drug Dependence	0.02	0.15	0.02	0.14
Post-Traumatic Stress Disorder	0.14	0.35	0.14	0.35
Poor Health	0.21	0.41	0.21	0.41
Caregiven child has learning/mental/phys health problem	0.18	0.38	0.18	0.38
Severe abuse in last year	0.16	0.36	0.15	0.36
Social Phobia	0.08	0.26	0.07	0.26
No car or license	0.35	0.48	0.35	0.48
Read instructions/reports	0.19	0.39	0.19	0.39
Wave 2 Welfare Stayer	0.68	0.47	0.66	0.47
If less than HS ed	0.31	0.46	0.31	0.46
If less than 4 skills	0.21	0.41	0.21	0.41
4+ Welf., Sex, or Race discrim. Experiences	0.14	0.34	0.14	0.34
Worked less that 20% of yrs since 18	0.14	0.35	0.14	0.35

Table 6.3
Wave 3 Summary Statistics - Weighted and Unweighted

	No Weights		With Weights	
	MEAN	STD	MEAN	STD
Age	29.98	7.44	29.75	7.35
Race (1=Black)	0.56	0.50	0.56	0.50
Alcohol Dependence	0.02	0.14	0.02	0.14
Major Depression Disorder	0.18	0.39	0.18	0.38
General Anxiety Disorder	0.11	0.31	0.10	0.30
Drug Dependence	0.03	0.18	0.03	0.17
Post-Traumatic Stress Disorder	0.14	0.35	0.14	0.35
Poor Health	0.22	0.42	0.21	0.41
Caregiven child has learning/mental/phys health problem	0.15	0.35	0.14	0.35
Severe abuse in last year	0.12	0.32	0.12	0.33
Social Phobia	0.08	0.28	0.08	0.27
No car or license	0.30	0.46	0.31	0.46
Learning disability	0.15	0.36	0.15	0.36
Read instructions/reports	0.19	0.39	0.19	0.39
Convicted of a crime	0.05	0.22	0.05	0.22
Wave 3 Welfare Stayer	0.56	0.50	0.54	0.50
If less than HS ed	0.31	0.46	0.31	0.46
If less than 4 skills	0.21	0.41	0.21	0.41
4+ Welf., Sex, or Race discrim. Experiences	0.14	0.35	0.14	0.34

Table 6.4
Wave 4 Summary Statistics - Weighted and Unweighted

	No Weights		With Weights	
	MEAN	STD	MEAN	STD
Age	30.08	7.47	29.76	7.36
Race (1=Black)	0.55	0.50	0.56	0.50
Alcohol Dependence	0.02	0.15	0.02	0.16
Major Depression Disorder	0.20	0.40	0.19	0.40
General Anxiety Disorder	0.12	0.32	0.11	0.32
Drug Dependence	0.03	0.18	0.03	0.18
Post-Traumatic Stress Disorder	0.15	0.36	0.15	0.36
Poor Health	0.24	0.43	0.23	0.42
Caregiven child has learning/mental/phys health problem	0.15	0.36	0.14	0.35
Severe abuse in last year	0.13	0.34	0.13	0.34
Social Phobia	0.09	0.28	0.08	0.27
no car or license	0.27	0.44	0.28	0.45
Learning disability	0.13	0.34	0.13	0.33
Read instructions/reports	0.20	0.40	0.19	0.40
Wave 4 Welfare Stayer	0.46	0.50	0.44	0.50
If less than HS ed	0.30	0.46	0.31	0.46
If less than 4 skills	0.21	0.41	0.20	0.40
4+ Welf., Sex, or Race discrim. Experiences	0.14	0.35	0.14	0.35
Worked less that 20% of yrs since 18	0.14	0.35	0.13	0.34

Table 6.5
Wave 5 Summary Statistics - Weighted and Unweighted

	No Weights		With Weights	
	MEAN	STD	MEAN	STD
Age	30.26	7.56	29.78	7.43
Race (1=Black)	0.55	0.50	0.56	0.50
Alcohol Dependence	0.03	0.16	0.03	0.16
Major Depression Disorder	0.22	0.41	0.20	0.40
General Anxiety Disorder	0.16	0.36	0.15	0.36
Drug Dependence	0.02	0.15	0.02	0.15
Post-Traumatic Stress Disorder	0.17	0.38	0.17	0.37
Poor Health	0.27	0.45	0.25	0.44
Caregiven child has learning/mental/phys health problem	0.16	0.36	0.15	0.36
Severe abuse in last year	0.12	0.33	0.13	0.34
Social Phobia	0.09	0.28	0.08	0.28
no car or license	0.23	0.42	0.23	0.42
Learning disability	0.13	0.34	0.13	0.33
Read instructions/reports	0.20	0.40	0.19	0.40
Wave 5 Welfare Stayer	0.29	0.45	0.26	0.44
If less than HS ed	0.30	0.46	0.31	0.46
If less than 4 skills	0.21	0.41	0.21	0.41
4+ Welf., Sex, or Race discrim. Experiences	0.15	0.35	0.14	0.35
Worked less that 20% of yrs since 18	0.14	0.35	0.13	0.34

Table 7 - Weighted and Unweighted Regressions

	Financial Strain - Extremely Difficult		Financial Strain - Extremely or Very Difficult		Severe Domestic Abuse		Drug or Alcohol Abuse	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
Number of Children	0.000	-0.002	-0.029*	-0.029*	0.000	0.004	-0.010	-0.013
	(0.011)	(0.011)	(0.014)	(0.014)	(0.010)	(0.011)	(0.010)	(0.010)
Any Mental Health Problems	0.062**	0.061**	0.090**	0.088**	0.066**	0.067**	0.101**	0.099**
	(0.018)	(0.019)	(0.023)	(0.024)	(0.017)	(0.018)	(0.017)	(0.019)
Drug or Alcohol Abuse	-0.016	-0.012	-0.032	-0.031	0.021	0.018		
	(0.023)	(0.025)	(0.029)	(0.030)	(0.022)	(0.024)		
Health Barrier	0.036	0.041	0.041	0.045	0.021	0.022	-0.021	-0.022
	(0.022)	(0.025)	(0.028)	(0.031)	(0.021)	(0.024)	(0.022)	(0.023)
Child Health Barrier	0.028	0.029	-0.011	-0.013	0.025	0.025	0.014	0.014
	(0.022)	(0.023)	(0.029)	(0.029)	(0.021)	(0.023)	(0.022)	(0.023)
Severe Domestic Abuse	0.021	0.026	0.058*	0.066*			0.023	0.019
	(0.023)	(0.027)	(0.029)	(0.032)			(0.022)	(0.025)
Married	-0.049	-0.053	-0.204**	-0.198**	0.022	0.015	-0.005	-0.006
	(0.045)	(0.039)	(0.058)	(0.048)	(0.043)	(0.041)	(0.044)	(0.042)
Marriage Duration	-0.008	-0.006	0.019	0.017	-0.006	-0.006	0.016	0.018
	(0.016)	(0.014)	(0.021)	(0.017)	(0.015)	(0.011)	(0.016)	(0.017)
Subsequently Divorced	0.136	0.122	0.141	0.126	0.327**	0.331**	0.187*	0.207*
	(0.087)	(0.104)	(0.112)	(0.103)	(0.083)	(0.106)	(0.085)	(0.095)
Wave 3 Dummy	-0.025	-0.026	-0.061**	-0.058**	-0.037*	-0.035*	-0.029+	-0.027
	(0.017)	(0.017)	(0.021)	(0.022)	(0.016)	(0.017)	(0.016)	(0.017)
Wave 4 Dummy	-0.057**	-0.058**	-0.111**	-0.108**	-0.024	-0.025	-0.023	-0.025
	(0.018)	(0.016)	(0.023)	(0.022)	(0.017)	(0.017)	(0.017)	(0.018)
Wave 5 Dummy	-0.008	-0.011	-0.051*	-0.053*	-0.054**	-0.049**	-0.051**	-0.058**
	(0.020)	(0.020)	(0.025)	(0.026)	(0.019)	(0.019)	(0.019)	(0.019)
Constant	0.132**	0.133**	0.396**	0.386**	0.121**	0.115**	0.215**	0.222**
	(0.026)	(0.029)	(0.034)	(0.035)	(0.025)	(0.028)	(0.025)	(0.027)
Observations	2714	2714	2714	2714	2716	2716	2716	2716
R-squared	0.39	0.38	0.43	0.43	0.42	0.42	0.57	0.57

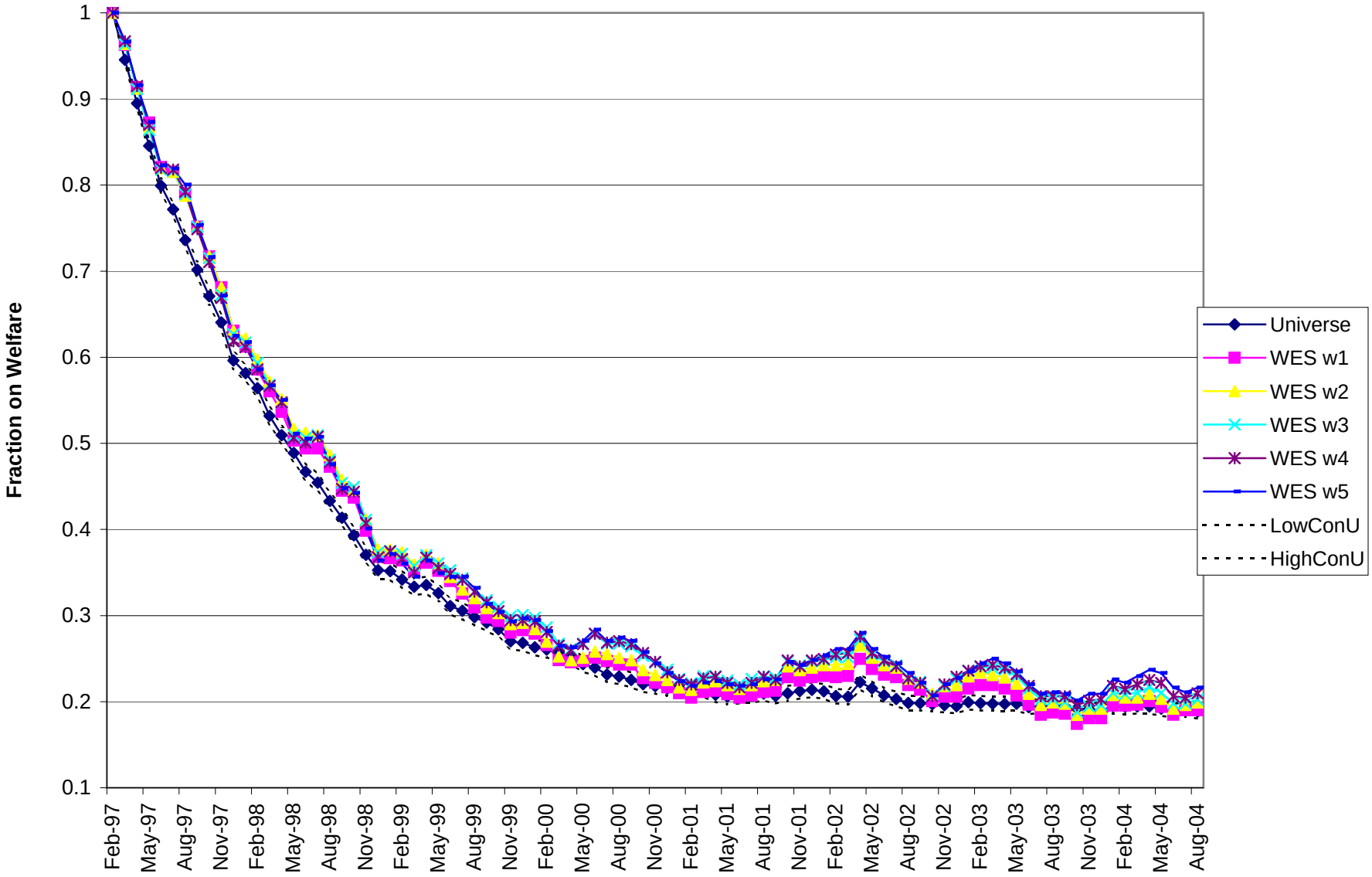
Standard errors in parentheses
Regressions include individual fixed effects
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 7 con't - Weighted and Unweighted Regressions

	Any Mental Health Problem		Income to Needs Ratio		Own Earnings		Others' Earnings	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
Number of Children	-0.012	-0.012						
	(0.013)	(0.013)						
Any Mental Health Problems			-0.037	-0.031	-58.201+	-54.850	-69.480+	-62.707
			(0.035)	(0.037)	(31.867)	(36.412)	(37.670)	(40.146)
Drug or Alcohol Abuse	0.158**	0.155**	0.047	0.046	-38.458	-33.549	62.578	56.492
	(0.027)	(0.030)	(0.044)	(0.051)	(40.006)	(41.000)	(47.291)	(53.660)
Health Barrier	0.066*	0.069*	-0.042	-0.041	-131.825**	-136.881**	-10.568	-14.182
	(0.027)	(0.029)	(0.043)	(0.035)	(38.964)	(38.884)	(46.060)	(37.845)
Child Health Barrier	0.031	0.027	-0.004	0.004	-51.625	-44.217	-31.912	-20.719
	(0.027)	(0.028)	(0.044)	(0.041)	(39.376)	(37.839)	(46.546)	(60.218)
Severe Domestic Abuse	0.107**	0.108**	-0.052	-0.058	-27.618	-30.159	-51.089	-58.432
	(0.028)	(0.030)	(0.045)	(0.044)	(40.558)	(38.319)	(47.944)	(49.589)
Married	-0.114*	-0.126*	0.303**	0.317**	-107.476	-97.077	850.712**	853.950**
	(0.055)	(0.056)	(0.089)	(0.106)	(79.910)	(92.962)	(94.463)	(143.306)
Marriage Duration	0.011	0.013	0.069*	0.056+	67.899*	60.838	158.954**	155.414**
	(0.020)	(0.019)	(0.032)	(0.032)	(28.623)	(42.139)	(33.836)	(48.157)
Subsequently Divorced	0.026	0.033	0.231	0.247	-78.072	-85.836	466.197*	524.643*
	(0.106)	(0.115)	(0.171)	(0.215)	(154.660)	(149.750)	(182.826)	(239.033)
Wave 3 Dummy	0.047*	0.041*	0.050	0.052	184.876**	183.817**	163.119**	164.803**
	(0.020)	(0.020)	(0.033)	(0.033)	(29.482)	(27.445)	(34.851)	(40.395)
Wave 4 Dummy	0.016	0.016	0.118**	0.127**	258.829**	264.053**	119.022**	124.668**
	(0.022)	(0.021)	(0.035)	(0.034)	(31.386)	(31.692)	(37.102)	(35.326)
Wave 5 Dummy	0.050*	0.046+	0.213**	0.214**	309.529**	323.624**	109.113**	103.333*
	(0.024)	(0.024)	(0.038)	(0.042)	(34.093)	(37.398)	(40.302)	(41.059)
Constant	0.281**	0.277**	1.052**	1.051**	590.294**	595.102**	290.769**	293.765**
	(0.032)	(0.033)	(0.026)	(0.024)	(23.594)	(23.269)	(27.890)	(27.612)
Observations	2716	2716	2716	2716	2716	2716	2716	2716
R-squared	0.50	0.50	0.47	0.48	0.52	0.54	0.55	0.55

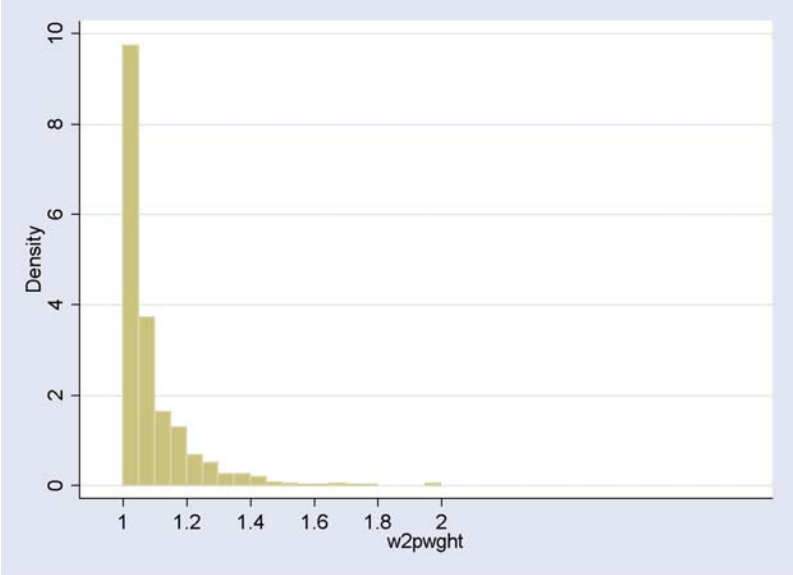
Standard errors in parentheses
Regressions include individual fixed effects
+ significant at 10%; * significant at 5%; ** significant at 1%

Figure 1: Welfare usage over time - FIA universe and WES samples

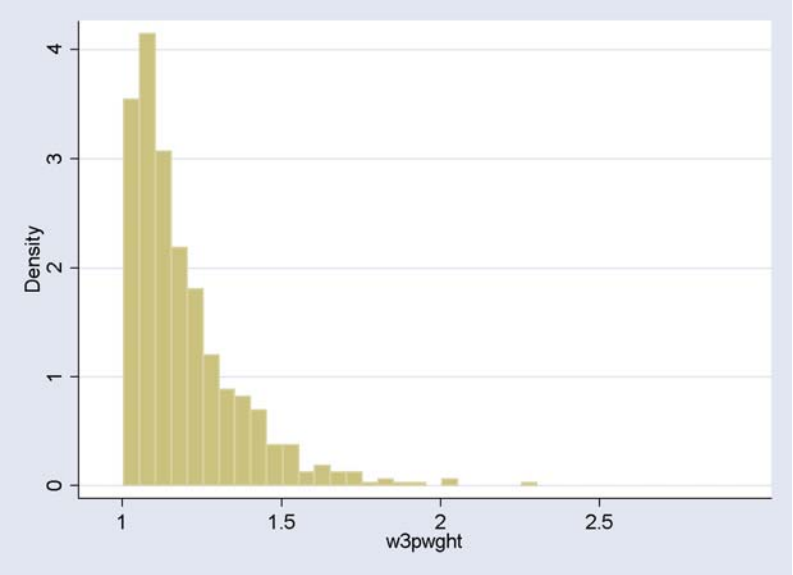


Appendix Figure 1 – Histograms of Propensity Score Weights by Wave

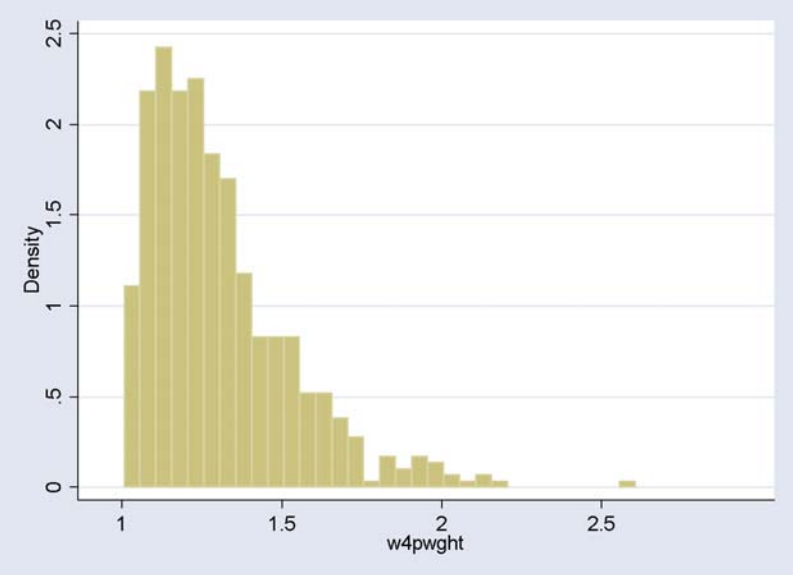
Wave 2 Weights



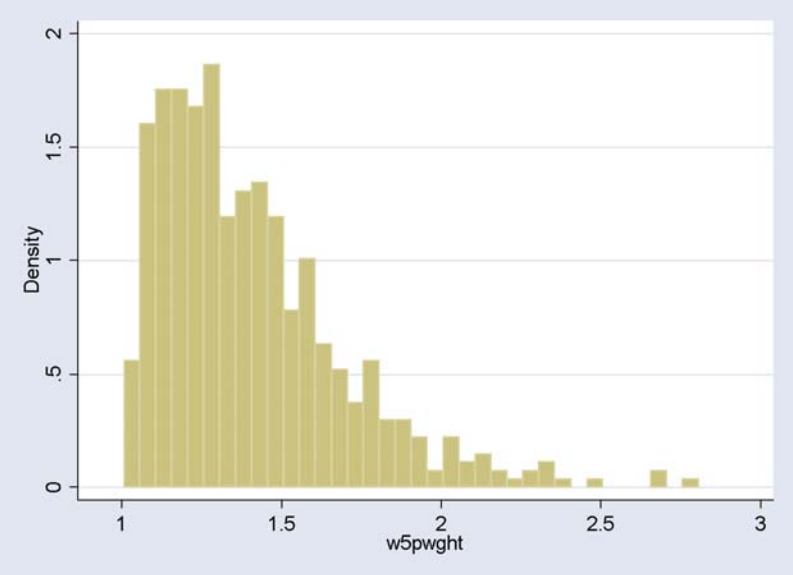
Wave 3 Weights



Wave 4 Weights



Wave 5 Weights



Appendix Table 1.2
Probit Predicting Response in Wave 2

Variable	Estimate	Std Err	Signif. at 95%?
Intercept	0.02	0.96	
Age	0.04	0.01	*
Race (1=Black)	-0.44	0.19	*
W2 Welfare Recepient	0.76	0.18	*
Partner in Home	0.32	0.21	
no car or license	-0.22	0.18	
any mental health barrier	-0.03	0.40	
Alcohol Dependence	6.21	14479.37	
Drug Dependence	6.33	13215.01	
Major Depression Disorder	0.19	0.37	
Post-Traumatic Stress Disorder	0.03	0.34	
If any physical threats	0.19	0.25	
If any reports of violence	-0.05	0.25	
If more than HS education	-0.19	0.20	
If less than HS ed	-0.17	0.21	
Food insuffiency	0.01	0.20	
Mastery scale (skills)	0.02	0.03	
Num. Discrimination incidents in hiring	0.02	0.10	
Talk to customer face-to-face	-0.13	0.29	
Talk to customer over phone	0.01	0.21	
read instructions/reports	0.15	0.19	
writes letters/memos	0.05	0.20	
works with computer	-0.31	0.20	
works with electronics	0.20	0.30	
arithmetic	-0.51	0.29	
fill out forms	0.22	0.21	
monitor eq'pmt	0.03	0.18	
supervise others	-0.07	0.18	
baby-sat for pay	0.21	0.17	
did housekeeping	0.07	0.24	
styled hair	0.73	0.27	*
sold things out of home	0.26	0.37	
did odd jobs	-1.16	0.28	*
pawned personal items	-0.41	0.22	
taken food w/o paying	5.89	25975.90	
engaged in illegal activity	-0.61	0.80	
sold food stamps	0.04	0.53	
Currently working	0.40	0.17	*
report: health fair/poor	0.03	0.21	
Stressful life events (scale)	0.01	0.06	
Physical limitation scale	-0.01	0.02	

Number of Observations:	753
Log Likelihood:	-171.35

Appendix Table 1.3
Probit Predicting Response in Wave 3

Variable	Estimate	Std Err	Signif. at 95%?
Intercept	2.25	0.96	*
Age	0.00	0.01	
Race (1=Black)	0.11	0.17	
W3 Welfare Recepient	0.29	0.17	
Partner in Home	0.15	0.17	
no car or license	-0.30	0.18	
any mental health barrier	0.32	0.33	
Alcohol Dependence	-0.39	0.63	
Drug Dependence	0.45	0.65	
Major Depression Disorder	-0.31	0.30	
Post-Traumatic Stress Disorder	-0.31	0.30	
If any physical threats	-0.01	0.34	
If any reports of violence	0.08	0.30	
If more than HS education	0.45	0.20	*
If less than HS ed	0.04	0.18	
Food insuffiency	0.24	0.20	
Mastery scale (skills)	0.00	0.02	
Num. Discrimination incidents	0.02	0.06	
Talk to customer face-to-face	-0.01	0.23	
Talk to customer over phone	-0.05	0.22	
read instructions/reports	-0.24	0.20	
writes letters/memos	0.17	0.20	
works with computer	-0.11	0.20	
works w/ electronics	-0.06	0.23	
arithmetic	-0.05	0.24	
fill out forms	0.05	0.20	
monitor eq'pmt	-0.25	0.17	
supervise others	-0.24	0.18	
baby-sat for pay	-0.14	0.17	
did housekeeping	0.04	0.21	
styled hair	0.13	0.23	
did odd jobs	-0.06	0.32	
pawned personal items	-0.33	0.21	
taken food w/o paying	709.65	165150.60	
engaged in illegal activity	-0.08	0.61	
sold food stamps	-0.23	0.43	
Stressful life events (scale)	-0.11	0.06	*
Social support scale	0.08	0.04	
report: health fair/poor	0.21	0.21	
currenly or recently pregnant	-0.03	0.22	
Physical limitation scale	-0.05	0.02	*
Currently working	0.43	0.19	*

Number of Observations:	693
Log Likelihood:	-182.908

Appendix Table 1.4
Probit Predicting Response in Wave 4

Variable	Estimate	Std Err	Signif. at 95%?
Intercept	0.69	0.90	
Age	0.02	0.01	
Race (1=Black)	-0.17	0.18	
W4 Welfare Recepient	0.35	0.18	*
Partner in Home	0.20	0.17	
no car or license	-0.21	0.19	
any mental health barrier	-0.27	0.27	
Alcohol Dependence	7.20	11406.55	
Drug Dependence	-0.46	0.54	
Major Depression Disorder	0.79	0.32	*
Post-Traumatic Stress Disorder	0.27	0.32	
If any physical threats	-0.27	0.30	
If any reports of violence	-0.09	0.27	
If more than HS education	0.05	0.19	
If less than HS ed	-0.11	0.20	
Food insuffiency	-0.08	0.20	
Mastery scale (skills)	-0.02	0.03	
Num. Discrimination incidents	0.19	0.18	
Talk to customer face-to-face	0.20	0.23	
Talk to customer over phone	0.10	0.21	
read instructions/reports	0.38	0.23	
writes letters/memos	-0.29	0.21	
works with computer	-0.03	0.23	
arithmetic	-0.34	0.23	
fill out forms	-0.10	0.24	
supervise others	0.06	0.19	
baby-sat for pay	0.23	0.21	
did housekeeping	-0.18	0.24	
styled hair	0.32	0.27	
did odd jobs	-0.04	0.33	
pawned personal items	-0.26	0.27	
taken food w/o paying	-0.60	0.50	
engaged in illegal activity	6.92	13472.81	
sold food stamps	-0.49	0.65	
Currently working	0.20	0.19	
report: health fair/poor	-0.02	0.19	
Currently or recently pregnant	0.10	0.41	
physical limitation scale	0.01	0.02	

Number of Observations: 632
Log Likelihood: -167.371

Appendix Table 1.5
Probit Predicting Response in Wave 5

Variable	Estimate	Std Err	Signif. at 95%?
Intercept	0.94	1.13	
Age	0.03	0.01	*
Race (1=Black)	-0.18	0.20	
W5 Welfare Recepient	0.34	0.24	
Partner in Home	0.13	0.19	
no car or license	-0.07	0.22	
any mental health barrier	0.00	0.36	
Alcohol Dependence	-0.13	0.79	
Drug Dependence	-0.47	0.63	
Major Depression Disorder	0.25	0.38	
Post-Traumatic Stress Disorder	0.08	0.37	
If any physical threats	0.32	0.41	
If any reports of violence	-0.38	0.37	
If more than HS education	0.01	0.22	
If less than HS ed	-0.30	0.24	
Food insuffiency	-0.02	0.28	
Mastery scale (skills)	-0.10	0.04	*
Num. Discrimination incidents	0.00	0.22	
Talk to customer face-to-face	-0.33	0.31	
Talk to customer over phone	0.45	0.25	
read instructions/reports	0.03	0.28	
writes letters/memos	0.23	0.24	
works with computer	-0.55	0.31	
arithmetic	0.27	0.28	
fill out forms	0.08	0.28	
supervise others	0.01	0.21	
baby-sat for pay	0.76	0.33	*
did housekeeping	0.20	0.34	
styled hair	0.36	0.30	
did odd jobs	-0.28	0.35	
pawned personal items	0.36	0.40	
taken food w/o paying	-0.42	0.57	
engaged in illegal activity	5.87	14178.53	
sold food stamps	-0.11	0.69	
Currently working	0.15	0.22	
report: health fair/poor	0.40	0.24	
Currently or recently pregnant	0.13	0.39	
physical limitation scale	0.06	0.03	*

Number of Observations: 577
Log Likelihood: -126.175