DID EXPANDING MEDICAID AFFECT WELFARE PARTICIPATION?

JOHN C. HAM and LARA D. SHORE-SHEPPARD*

In a widely cited 1995 paper, Aaron Yelowitz concluded that Medicaid eligibility expansions for children were associated with increased labor force participation and reduced welfare participation among single mothers. The authors of the present study, using data from the 1988–96 Current Population Surveys, re-examine the evidence presented by Yelowitz. They find that Yelowitz's results resulted from two factors: he imposed a restriction on the parameter estimates not predicted by theory and rejected in the data, and he used only one of two income tests that families must pass to be eligible for welfare. The authors conclude that there is no evidence detectable in the CPS data of a relationship between welfare or labor force participation and the Medicaid income limits.

Since the advent of "welfare reform" in 1996, which replaced the Aid to Families with Dependent Children (AFDC) program with Temporary Assistance to Needy Families (TANF), there has been strong interest in factors that help single-headed families leave cash assistance. One factor that has received some attention is the link between cash assistance and publicly provided health insurance (Medicaid). Until the late 1980s, virtually the only way for a low-income woman or child to receive Medicaid was to participate in AFDC. Since leaving AFDC meant losing one's health insurance as well as cash support, and since many low-wage jobs do not offer health insurance, the connection between AFDC and Medicaid provided an additional incentive for a woman to remain on welfare, even if she might otherwise choose to participate in the labor force.

Beginning in the late 1980s, however, Medicaid coverage was expanded to children in families with incomes well above the AFDC limits. Separate Medicaid eligibility income limits were established that were linked to the poverty line rather than to a state's AFDC limits, permitting children in low-income working-parent families to qualify for Medicaid despite their

*John Ham is Professor of Economics at Ohio State University and IZA Research Associate. Lara Shore-Sheppard is Associate Professor of Economics at Williams College and NBER Faculty Research Fellow. This research was supported by grants from the National Institute of Child Health and Human Development (Grant No. R01 HD39369-01A1) and the National Science Foundation (Grant No. SBR-9809546). The authors thank Eileen Kopchik and Noam Yuchtman for excellent research assistance, Aaron Yelowitz for making his programs and data available, and Serkan Ozbeklik, Lucie Schmidt, and seminar participants at the Orley Ashenfelter Festschrift, Williams College, and U.C.–Berkeley for helpful comments on earlier drafts.

Copies of the programs and data used to generate the results in this paper are available from Lara Shore-Sheppard at the Department of Economics, Fernald House, Williams College, Williamstown, MA 01267.

Industrial and Labor Relations Review, Vol. 58, No. 3 (April 2005). © by Cornell University.
0019-7939/00/5803 $01.00

family's ineligibility for AFDC. This break in the link between AFDC and Medicaid for children has potentially made it easier for families to leave welfare, since at least some of the children in the families can keep their health insurance following an exit from welfare. In this paper, we investigate whether the availability of Medicaid coverage for children unconnected to AFDC led to increased labor force participation and reduced welfare participation among single mothers. This issue is particularly relevant for current policy, since under TANF, Medicaid eligibility determination is separate from cash assistance eligibility determination. Our paper provides evidence on whether this separation is likely to result in greater labor force participation.

Previous work on the question of whether Medicaid eligibility affected welfare participation has led to mixed results. Early researchers typically found little evidence that eligibility for Medicaid affected labor force or welfare participation among single women. However, these researchers faced the difficulty of separating the impact of Medicaid from the direct impact of AFDC, because prior to the expansions Medicaid was rarely received in the absence of cash welfare payments. In a 1995 paper widely cited in both academic and policy circles, Aaron Yelowitz used the separation between AFDC and Medicaid eligibility for children induced by the Medicaid expansions to examine this question. Using data from the 1989–92 March Current Population Surveys (CPS), he found that increasing Medicaid income limits lowered the probability that a woman with dependent children received welfare and increased the probability that she participated in the labor force. Given that his analysis is based on variation in Medicaid eligibility separate from variation in AFDC eligibility, his results have been considered much more convincing than those of earlier researchers.

However, in recent work using data from the Survey of Income and Program Participation (SIPP), we found no evidence that higher Medicaid income limits increased the transition rate out of welfare, nor did we find that they reduced the transition rate into welfare (Ham and Shore-Sheppard 2001). To address the possibility that our results reflected a lack of power in the data to estimate a multiple state duration model, we then examined the static relationship between Medicaid income limits and welfare participation in the SIPP analogous to that examined by Yelowitz. Again we did not find a statistically significant effect of increasing the Medicaid income limits on welfare participation.

To understand why the SIPP and the CPS produce different results, in this paper we re-examine the evidence from the CPS found in Yelowitz (1995). Our contribution is three-fold. First, we examine the restriction imposed by Yelowitz's specification that the Medicaid income limits and AFDC income limits have effects that are equal in magnitude but opposite in sign. We show that this constraint on the parameters is not predicted by theory, since, for example, it implies that AFDC benefits had no effect on AFDC participation prior to the Medicaid expansions. We then test this restriction empirically using the CPS data. Second, we note that Yelowitz incorrectly calculated the AFDC income limits in his analysis. To be eligible for AFDC, families must pass two income tests—a "net test" that income less disregards be below a limit set by the state, and a "gross test" that income be below another state-set limit. In his analysis, Yelowitz ignored the gross test, despite the fact that it is binding for some families, particularly those with multiple children. We calculate the AFDC income limits using both statutory tests. Finally, we extend the data set to the period 1988–96 to capture additional expansions in Medicaid eligibility.

Expansions in Medicaid Eligibility

Historically, eligibility for Medicaid among low-income single-parent families was restricted to those whose incomes were low enough to qualify for AFDC. AFDC eligibility required that the family's income and resources be less than state-established income limits, most of which were well below the federal poverty line. This meant that few working mothers were able to qualify for AFDC and Medicaid. It also meant that if a woman were to leave welfare, she and her children would lose their Medicaid coverage. Starting in the mid-1980s, a series of federal laws uncoupled Medicaid eligibility from AFDC eligibility, expanding the population eligible for Medicaid to include poor pregnant women and children ineligible for AFDC. Under the expansions, Medicaid eligibility determination for children differed from AFDC eligibility determination in three fundamental ways: the child eligibility limits were linked to the federal poverty line rather than to the AFDC limits, there were no family structure requirements, and eligibility was determined at the individual, rather than family, level.

In the Omnibus Budget Reconciliation Acts (OBRAs) of 1986 and 1987, states were given the authority to raise the income thresholds for Medicaid coverage of infants, young children, and pregnant women above the AFDC level. In addition, OBRA 1987 required states to cover all children born after September 30, 1983, who met AFDC income standards, regardless of their family composition. The most far-reaching expansions took place as a result of OBRA 1989 and OBRA 1990. OBRA 1989 required coverage of pregnant women and children up to age 6 with family incomes below 133% of the federal poverty level, and OBRA 1990 required states to cover children born after September 30, 1983, with family incomes below 100% of the federal poverty level. States were permitted to expand coverage further, within federal guidelines for age and family income.[1] The form of the expansions thus provides useful variation in eligibility along several dimensions: across states because of variation in AFDC eligibility and state-optional expansions, over time because the expansions were phased in, by child age because younger children became eligible sooner or at a higher income level, and by family income. Following Yelowitz, we exploit this variation in our analysis.

[1]See Shore-Sheppard (2003) for a more detailed discussion of the expansions.

Previous Literature

The question of whether Medicaid provides an additional incentive for a woman to remain on welfare rather than participate in the labor force has been studied by several previous researchers. Because Medicaid was formerly obtained solely through participation in welfare, studies prior to the expansions confront the question of how to identify the marginal impact of Medicaid on labor supply. To address this problem, Blank (1989) and Winkler (1991) calculated a state-specific value of Medicaid and included it in individual AFDC participation, labor force participation, and hours worked equations. They found generally small and usually statistically insignificant effects of the value of Medicaid.

Moffitt and Wolfe (1992) developed a family-specific proxy for the value of Medicaid and included it in cross-sectional probit equations of AFDC participation and employment. They found that more valuable Medicaid benefits led to higher rates of AFDC participation and lower rates of labor force participation. However, the value of Medicaid proxy used in their study may have been capturing other unobserved differences between families that affect labor force and welfare participation, such as tastes or the wage available to the mother. In fact, when they allowed the effect of Medicaid to differ for families with low and high values of Medicaid, they found that only families with high expected medical expenditures altered their AFDC participation or employment decisions in response to Medicaid availability. Consequently, these results may not indicate what the effect of de-linking Medicaid and AFDC for the welfare population as a whole would be.

Yelowitz (1995) was the first to take advantage of the separation between AFDC and Medicaid eligibility induced by the Medicaid expansions. Using four years of

March CPS data, from 1989 to 1992, he estimated whether the probabilities that a single mother is in the labor force or is on welfare were affected by the Medicaid expansions. Since the Medicaid expansions primarily covered children, rather than the mothers themselves (an exception being for mothers who are pregnant), he used the Medicaid income limits facing the mother's youngest child to capture the extent to which the expansions affected a particular woman. He expressed both the Medicaid income limits for the mother's youngest child and the AFDC income limits as a percentage of the federal poverty line to obtain the variables MEDICAID% and AFDC%, respectively. MEDICAID% was set equal to zero for periods when one could only obtain Medicaid through AFDC or if no child in the family was age-eligible for Medicaid given the expansions.[2] Yelowitz then parameterized the expansions as

$$(1) \quad \text{GAIN\%} = \max(\text{MEDICAID\%} - \text{AFDC\%}, 0).$$

MEDICAID% depends on the age of the child, the state of residence, and the year. Nonzero levels of MEDICAID% typically range from 75% to 185% of the poverty line. AFDC%, which is the maximum income a family could earn and still receive AFDC benefits, depends on family size, family age structure, state of residence, and year. Levels of AFDC% are typically well below 100% of the poverty line, although because of work expense and child care deductions it is possible for AFDC% to exceed 100% in particularly generous states.

To gain better intuition about this specification, define a variable MED* to be equal to the income limit applying to Medicaid eligibility divided by the poverty line. MED* equals AFDC% before the expansions or if no child in the family is age-eligible for Medicaid. If any child in the family is age-eligible for Medicaid, it equals the Medicaid expansion income limit applying to the youngest child divided by the poverty line. Thus GAIN% can also be written as

$$(2) \quad \text{GAIN\%} = \text{MED}^* - \text{AFDC\%}.$$

From this specification, it can be seen that GAIN% increases not only when the Medicaid eligibility limits increase, but also when AFDC income limits decline, and thus it captures the effect of AFDC as well as of Medicaid.

Yelowitz estimated probit models of labor force participation and welfare participation including GAIN%, the number of children in the family under six years old, and characteristics of the mother including age, marital status (divorced, separated, or never married), race, education, and central city residence. He also included dummy variables for state, year, family size, age of the youngest child, and an interaction between age of the youngest child and year. These dummies are intended to capture other factors in states or changes over time that could affect welfare and labor force participation. He also estimated models including interactions between state and year and between youngest child's age and state to reduce the possibility that unobserved factors are the source of any measured effect of GAIN%.

These models showed a statistically significant coefficient on GAIN% for both labor force and welfare participation in virtually all specifications, suggesting that expanding Medicaid reduced the probability of welfare participation by 1.2 percentage points and increased the probability a woman was in the labor force by 0.9 percentage points. However, from the specification of GAIN% in (2), it can be seen that Yelowitz was making two implicit assumptions. First, before the expansions or if no child was age-eligible in the family, he implicitly assumed that AFDC% did not affect the probability that a woman was on welfare. Second, if a child was age-eligible, he implicitly assumed that increasing AFDC%, holding GAIN% constant, did not affect the probability that a woman was on welfare. We examine these restrictions from both theoretical and empirical perspectives below.

[2]By age-eligible we mean that the child would be eligible for Medicaid given his or her age if the family's income was below the Medicaid income limit for that age.

Theoretical Predictions and Basic Econometric Model

To derive predictions about welfare and labor force participation behavior when Medicaid can be received separately from welfare, we consider the optimization problem of an individual with dependent children who (i) can collect welfare and receive Medicaid, (ii) can work with earnings up to the Medicaid limit and still receive Medicaid, and (iii) can work with earnings above the Medicaid limit and not receive Medicaid. To simplify the discussion at this stage, we ignore three institutional features: a fixed amount plus a certain level of child care expenses (the disregard) can be deducted from income before welfare benefits are reduced; the mother will lose her Medicaid coverage when she leaves AFDC, as may some of her children; and earned income must be no higher than 1.85 times the state-set "need standard" (the gross test). We also assume that the individual has been earning income while on welfare for at least four months, so that any earnings (above the disregard) are effectively taxed at 100%. Finally, we assume that there are no fixed costs of participation. We discuss relaxing each of these assumptions below; unless otherwise noted, relaxing these assumptions does not affect our theoretical predictions. We focus on AFDC participation in what follows, but the results are easily extended to labor force participation.

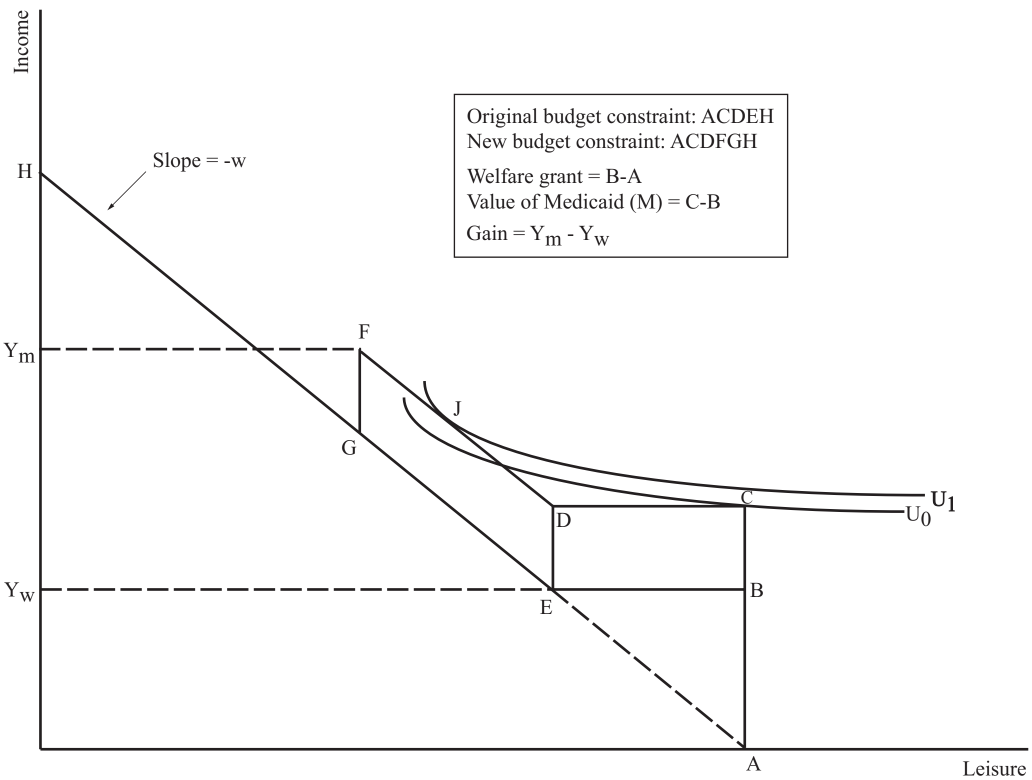
If the consumer does not work in the labor market, she receives income Y_w and Medicaid services worth αM. M represents the dollar value of Medicaid, while α is a parameter indicating the value the individual places on the insurance ($0 \leq \alpha \leq 1$). If $\alpha = 1$, Medicaid is worth the same to the individual as it costs to provide, while if $\alpha = 0$, the individual places no value on having Medicaid. For simplicity, in the following discussion we assume $\alpha = 1$. (We might expect α to be less than 1 since families can obtain emergency treatment for their children in the absence of Medicaid coverage.) Figure 1 shows the relevant budget constraint. For clarity in the Figure, M (the distance $C - B$) is shown to be larger relative to Y_w (the distance $B - A$) than it would be for a typical family, even assuming $\alpha = 1$. Since we assume for now that the woman is subject to a 100% tax rate, Y_w equals both the benefit level and the break-even level. Prior to the Medicaid expansions, the family loses its Medicaid once it leaves welfare, and the overall budget constraint is *ACDEH*. After the Medicaid expansions, the family can keep its Medicaid benefits as long as its earnings are below Y_m. The effective budget constraint is *ACDFGH*. Figure 1 shows the indifference curves for an individual who would not work in the absence of the Medicaid expansions (with an equilibrium at *C*), but does work (with an equilibrium at *J*) after the expansions.[3]

Since the budget constraint is not differentiable, and because the opportunity set is not compact, we use graphical analysis to calculate the comparative static results for this individual. In the interest of space, we do not show all of the graphs here, and instead describe the results briefly (see Ham and Shore-Sheppard 2003 for the full graphical analysis). Raising welfare benefits increases the amount of income an individual has while working few or no hours. Consequently, an increase in welfare benefits may induce some individuals to become recipients, but it will never induce a recipient to leave welfare. Conversely, increasing the Medicaid income limit increases the resources available to an individual while working. This increase will not induce a non-recipient to enter welfare, but it may induce some individuals to leave welfare. Thus we expect that the probability of being on welfare will be positively related to the level of welfare benefits, and negatively related to the Medicaid income limit.

Under our assumptions, raising the wage will induce some women to leave welfare but will not induce anyone to enter welfare. However, this unambiguous prediction of the wage effect is affected by our simplifications. If we were to assume that an individual had not been earning income while

[3]See Yelowitz (1995), Figures I and II.

Figure 1. Medicaid Expansions Induce an Individual to Leave Welfare.



on welfare and thus the effective tax rate on earnings while on welfare was less than 100%, the effect of a change in the wage on welfare participation would be ambiguous.

On the basis of this analysis, we expect the probability an individual is on welfare to depend positively on the level of welfare benefits as a percentage of the poverty line y_{wi}, negatively on the Medicaid income limit as a percentage of the poverty line y_{mi}, and negatively on the level of the wage w_i, as well as on demographic and demand variables X_i.[4] Thus we have

$$I_i^* = \gamma_0 + \gamma_1 y_{mi} + \gamma_2 y_{wi} + \gamma_3 w_i + \gamma_4 X_i + e_i. \tag{3}$$

Since the wage is unobserved, we assume that it depends on variables Z_i:

$$w_i = \beta Z_i + u_i. \tag{4}$$

We assume that Z_i does not contain the Medicaid income limit Y_{mi} or the level of welfare benefits Y_{wi}. When we substitute (4) into (3) and let X_i^* denote the unique elements of Z_i and X_i, the index function determining welfare participation becomes[5]

$$I_i^* = \mu_0 + \gamma_1 y_{mi} + \gamma_2 y_{wi} + \mu X_i^* + \varepsilon_i. \tag{5}$$

[4]Uppercase values of Y represent dollar amounts while lowercase values of y represent dollar amounts divided by the federal poverty line. One can interpret dividing by the poverty line as deflating by a price index for low-income families.

[5]An individual participates in welfare if $I_i^* > 0$. For a more structural approach to the issue of participating in income maintenance programs, see Ashenfelter (1983).

This equation, which is the basis for our empirical estimates, shows that welfare participation is a function of the Medicaid income limit and the level of welfare benefits, both expressed as a fraction of the poverty line, and demographic and demand variables, some of which determine the wage.

Yelowitz estimated a restricted version of (5) that constrained y_{mi} and y_{wi} to have coefficients that were equal in absolute value but opposite in sign, that is, $\gamma_1 = -\gamma_2$. This constraint has two implications. First, if the youngest child is age-eligible for Medicaid, welfare benefits do not affect the probability of being on welfare, conditional on the value of GAIN% ($y_{mi} - y_{wi}$) staying constant. Second, if no child is age-eligible, then increasing welfare benefits will not induce anyone to enter welfare. We now investigate whether these implications are consistent with our theoretical model.

As the counterexample in Figure 2 shows, the first restriction is not, in general, implied by the theoretical model. Here we show that an equal increase in Y_{mi} and Y_{wi} (thus keeping GAIN% constant) affects behavior and thus the Yelowitz restriction does not hold. In this example the individual originally has a tangency at *J* on the segment *DF* of the budget constraint, where the overall budget constraint is *ACDFGH*. When the levels of Y_{mi} and Y_{wi} are increased by the same amount, the budget constraint becomes *AKD'F'G'H*. For a sufficiently high increase in Y_{mi} and Y_{wi}, the individual moves to point *K* where she does not work. The intuition is straightforward: since the individual originally has a tangency on the segment *DF*, increasing the Medicaid limit does not benefit her. On the other hand, a sufficient increase in Y_{wi}, such as that shown in the figure, allows her to reach a higher indifference curve by entering welfare.

It is straightforward to show that the second implication does not hold either. If no child is age-eligible for Medicaid, we have the textbook AFDC case. It is well known that increasing AFDC benefits in this case will encourage some individuals to enter welfare, but will not encourage anyone to leave welfare. Thus both of the implications of Yelowitz's restriction are inconsistent with the theoretical predictions of a standard model of labor supply and program participation.

Allowing for Important Institutional Features

The actual budget constraint is somewhat more complicated than this stylized model indicates.[6] First, individuals face fixed costs of labor force participation in the form of work and day care expenses. Second, they are allowed to deduct a disregard equal to a constant dollar amount, *A*, plus actual day care expenses *D* (up to a per-child limit), before their earnings are taxed at 100%. In this case maximum feasible earnings become $Y^*_{wi} = Y_{wi} + A + D$, and we use this variable (divided by the poverty line) in our index function (5) instead of y_{wi}.

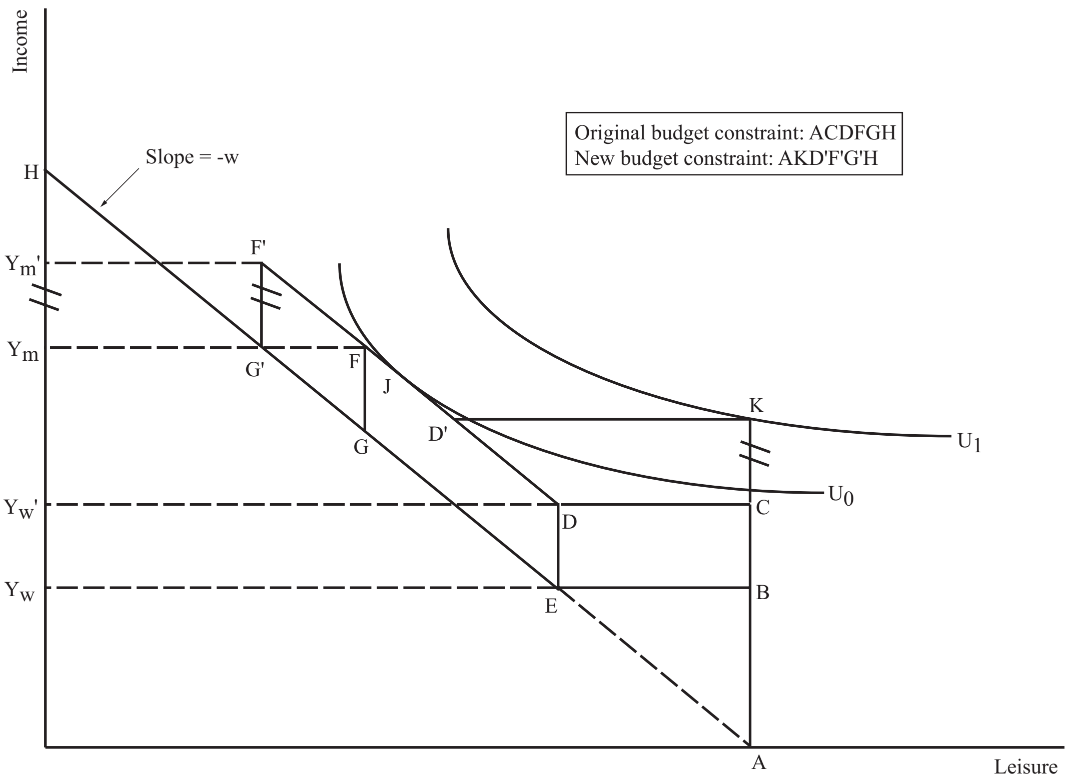
Third, as noted above, the mother will lose her Medicaid coverage when she leaves AFDC (as may some of her children). In terms of Figure 1, this will cause the line segment *DF* to shift down by the amount that the mother values the portion of Medicaid coverage only available through AFDC. This shift creates a notch at *D*.

Fourth, in the first four months of earnings while on welfare, participants are permitted to disregard an additional fraction *k* of earnings before the tax rate is applied. Countable income (the income subtracted from the state's "payment standard" to determine the benefit) in the first four months is thus $(1 - k)$ times an individual's earnings less other disregards, and the maximum feasible income becomes Y^{**}_{wi}, which equals $Y_{wi}/(1-k) + A + D$ before October 1989 and $(Y_{wi} + A + D)/(1-k)$ after October 1989.[7] If we assume, as did Yelowitz, that the first

[6] It is straightforward to show that none of these modifications affect the theoretical predictions discussed above.

[7] The Family Support Act of 1988 changed the calculation of benefits so that the income not subject to the "tax" is calculated before applying the disregards, increasing the possible benefit level.

Figure 2. Increasing Benefits, Holding Gain Constant, Induce the Individual to Enter Welfare.



four months' maximum feasible earnings is the relevant amount, then we would use Y^{**}_{wi} (divided by the poverty line) in the index function (5).

Finally, there is also a gross test, which requires that maximum feasible earnings not exceed 1.85 times the state-determined "need standard" (NS). Again assuming that the maximum feasible earnings for the first four months of working while on welfare is the relevant amount, we use Y^{***}_{wi} = minimum(1.85NS, Y^{**}_{wi}), divided by the poverty line, in (5). This is the variable *AFDC%*. Yelowitz ignored the gross test in calculating maximum feasible income and simply used Y^{**}_{wi} divided by the poverty line in calculating GAIN%, which is inappropriate.

Data

Following the previous literature, we use several years of the March Current Population Survey—from 1988 to 1996—to examine the effect of the expansions. The March CPS surveys many households, providing the largest available data set of single mothers containing information on welfare and labor force participation, demographics, and family structure. To ensure comparability between our results and those of Yelowitz, we use the same sample selection criteria he did—single mothers between the ages of 18 and 55 with at least one child under 15 present, not receiving Medicare or military health insurance, not reporting a handicap or ill health, and not a veteran.

Table 1. Sample Statistics.

	(1)	(2)	(3)	(4)	(5)	(6)
	1989–92 CPS			*1988–96 CPS*		
Description	*Means*[a]	*Fraction Nonzero*	*Mean if Nonzero*	*Means*	*Fraction Nonzero*	*Mean if Nonzero*
AFDC and Medicaid Measures (all as % of the poverty line):						
GAIN%, No Gross Test	4.74	0.19	24.54	13.05	0.39	33.35
GAIN% with Gross Test	11.42	0.32	35.40	21.81	0.49	44.34
AFDC%, No Gross Test	126.79	1	126.79	121.98	1	121.98
AFDC%, with Gross Test	105.31	1	105.31	103.13	1	103.13
MEDICAID% (expansion eligibility limit)	57.12	0.45	125.74	81.63	0.60	135.06
MED* (Medicaid eligibility limit)	116.73	1	116.73	124.94	1	124.94
Dependent Variables:	*1989–92 CPS*			*1988–96 CPS*		
Labor Force Participation	0.69			0.69		
AFDC Participation	0.33			0.33		
Demographics:						
Family Size	3.01			3.01		
No. Kids < Age 6	0.71			0.71		
Mother's Age	31.57			31.74		
Divorced	0.40			0.39		
Separated	0.20			0.20		
Black	0.36			0.35		
Central City	0.37			0.37		
Education	12.16			12.18		
Observations	16,022			36,628		

[a]All means are weighted using March supplement weights.

Source: The sample is composed of single mothers ages 18–55 with a child under 15 from the 1989–92 or 1988–96 March Current Population Surveys.

This results in a sample of 16,022 single mothers for the years 1989 to 1992 (the years used by Yelowitz) and 36,628 single mothers for the entire 1988 to 1996 sample.[8]

Again following Yelowitz, we use the youngest child's year of birth calculated from the reported age as of March of the survey year and assume that January is the birth month. We then impute the Medicaid expansion income threshold applying to this child as of December of the year preceding the survey year.[9] Dividing the imputed Medicaid income threshold for the mother's youngest child by the poverty line gives the variable MEDICAID%. Using state AFDC need and payment standards, we impute AFDC break-even levels for the year preceding the survey under Yelowitz's assumption that the family takes the full childcare disregard for all children under 18. We again follow Yelowitz in assuming that individuals make their decisions about

[8]Throughout the paper, years refer to the year in which the survey was conducted. Our sample size is slightly (40 observations) smaller than Yelowitz's because we lack information on state AFDC standards for families with more than nine members. We eliminate these families from our sample rather than assign them a value of GAIN% equal to 0, as Yelowitz did. Since we treat family size as exogenous, we do not create selection bias by deleting these families.

[9]We tried alternative birth month assumptions, including random assignment of birth month, and found little to no effect on estimated Medicaid eligibility levels or our results. Similarly, using the Medicaid income threshold as of July of the year preceding the survey did not affect our results.

welfare based on the first four months of earnings on welfare, which implies that the variable Y^{***}_{wi} is the relevant one.[10] This variable is divided by the poverty line as well, yielding AFDC%. MED* equals AFDC% if the Medicaid expansions are not in effect or the child is not age-eligible; otherwise it equals MEDICAID%. The variable GAIN% used by Yelowitz is thus GAIN% = MED* – AFDC%.

We estimate models for the two dependent variables used by Yelowitz: an indicator variable that takes the value of 1 if the individual reported working for at least one week during the reference year (the year preceding the March survey) and 0 otherwise, and another indicator variable that takes the value 1 if the individual reported receiving AFDC at any point during the reference year and 0 otherwise.[11] We have experimented with requiring longer work periods to constitute labor force participation, and though the coefficients on both MED* and AFDC% are reduced in absolute value in the labor force participation equation, the general pattern of results remains the same.[12] We report the results from the measures used by Yelowitz for greater comparability between the two studies.

Sample statistics broken down by time period, that is, 1989–92 and 1988–96, are presented in Table 1.[13] In the 1989–92 sample the mean of GAIN% is only 4.74% of the poverty line when the gross test is not used. It is very small because so many observations are zero, which occurs when the AFDC income limit is equal to or greater than the Medicaid expansion income limit MEDICAID%. This is relatively common when the gross test is not used. In fact, the mean value of the AFDC income limit exceeds the poverty line, even though no state has a need standard as high as the poverty line. This is due to the assumption of the full childcare disregard. Using the gross test reduces the mean value of the AFDC limit to 105.31% of the poverty line.

The results for the whole 1988–96 sample are broadly similar. Since there are later years of data in the whole sample, the expansions have been more fully phased in, raising the mean Medicaid expansion income limit to 82% of the poverty line from 57%. (It is 135% instead of 126% when only mothers whose youngest children are age-eligible for Medicaid are included.) The AFDC limits are lower in the whole sample than in the 1989–92 sample, suggesting a trend toward reduced AFDC benefits relative to the poverty line. The fact that AFDC limits (relative to the poverty line) may fall while the Medicaid income limit rises shows the importance of allowing AFDC and Medicaid to have separate effects, since using GAIN% alone will attribute the effect of any decreases in AFDC generosity on welfare participation to the Medicaid expansions.

Replication and Re-Analysis

The results from our replication of Yelowitz's work using the same years of data and the same specifications are presented in Table 2. The first and third columns of the table show Yelowitz's original results, while the second and fourth columns contain our attempt to replicate them. We are unable to replicate the results exactly, but our results are quite close to his.[14] These

[10]We also considered various alternative assumptions for the childcare disregard, and the possibility that the AFDC income limits should be based on those for months 5 and following of working while on welfare. None of these changes affected the estimated effect of the Medicaid expansions.

[11]Fewer than 1% of the respondents in our sample had imputed data for AFDC participation (and even fewer had imputed data for labor force participation). Nevertheless, we re-ran all of our models omitting individuals whose AFDC or labor force participation status had been imputed. The results did not change substantially.

[12]These results and the results from our other robustness checks are available upon request.

[13]In this table, the Medicaid and AFDC variables are in percentage terms, but in the estimates that follow, these variables are scaled to be fractions.

[14]At least part of the explanation for the inexact replication is that, as noted earlier, our treatment of families with more than nine members differs.

Table 2. Replication of Probit Models of Labor Force and AFDC Participation, 1989–92 March Current Population Surveys.[a]

	(1)	(2)	(3)	(4)
	Labor Force Participation[b]		*AFDC Participation*	
Variable	*Yelowitz Table IV, Col. (1)*	*Replication*	*Yelowitz Table IV, Col. (3)*	*Replication*
GAIN%[c]	0.384	0.393	–0.519	–0.564
	(0.151)	(0.121)	(0.154)	(0.124)
		[0.131]		[–0.192]
No. Kids < Age 6	–0.138	–0.148	0.180	0.193
	(0.029)	(0.029)	(0.029)	(0.030)
Mother's Age	0.060	0.062	–0.001	–0.004
	(0.012)	(0.012)	(0.012)	(0.012)
$Age^2/100$	–0.084	–0.085	–0.026	–0.021
	(0.018)	(0.019)	(0.018)	(0.017)
Divorced	0.386	0.371	–0.353	–0.352
	(0.031)	(0.031)	(0.031)	(0.031)
Separated	0.174	0.164	–0.236	–0.228
	(0.032)	(0.032)	(0.032)	(0.033)
Black	–0.071	–0.071	0.217	0.214
	(0.030)	(0.030)	(0.030)	(0.030)
Central City	–0.227	–0.216	0.189	0.190
	(0.027)	(0.027)	(0.027)	(0.027)
Education	–0.048	–0.048	0.134	0.135
	(0.022)	(0.022)	(0.022)	(0.022)
$Education^2$	0.009	0.009	–0.012	–0.012
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	16,062	16,022	16,062	16,022

[a]Standard errors in parentheses; marginal effects at the means in brackets.
[b]Regressions also include dummies for state, year, family size, age of the youngest child, and age of the youngest child interacted with year.
[c]GAIN% is measured as a fraction in this table and all following tables.
Source: The sample is composed of single mothers ages 18–55 with a child under 15 from the 1989–92 March Current Population Surveys.

results indicate that the variable GAIN%, which is the difference between the Medicaid and AFDC income limits (MED* and AFDC%, respectively), has a positive and statistically significant effect on labor force participation and a negative and statistically significant effect on AFDC participation. In addition, the control variables enter generally as would be expected.

In Table 3 we show the results from models using alternative specifications of Medicaid and AFDC.[15] For ease of comparison we include Yelowitz's original results and our replication in the first two columns. In the third column we show the effect of including the gross test in the calculation of the AFDC maximum income level. The magnitude of the estimated effect of GAIN% is reduced substantially for both labor force and AFDC participation, and the effect is no longer statistically sig-

[15]For each coefficient we show the relevant marginal effect in [ ]. As the coefficients on the demographic variables are essentially unchanged by any of the modifications to the specification, we omit their coefficients from all following tables. Full results are available upon request.

Table 3. Alternative Specifications of Medicaid and AFDC in Probit Models of Labor Force and AFDC Participation, 1989–92 March Current Population Surveys.[a]

Panel A: Models of Labor Force Participation[b]

Variable	*(1)* *Yelowitz Table IV, Col. (1)*	*(2)* *Replication*	*(3)* *With Gross Test*	*(4)* *Allow Different Effects for AFDC and Medicaid*	*(5)* *Different Effects with Gross Test*
GAIN%	0.384	0.393	0.105		
	(0.151)	(0.121)	(0.088)		
		[0.131]	[0.035]		
MED*[c]				0.204	0.058
				(0.123)	(0.091)
				[0.068]	[0.019]
AFDC%				–1.329	–0.322
				(0.160)	(0.132)
				[–0.443]	[–0.107]
χ^2 Test[d]				81.97	4.87
(p-value)				(0.000)	(0.027)

Panel B: Models of AFDC Participation

Variable	*(1)* *Yelowitz Table IV, Col. (3)*	*(2)* *Replication*	*(3)* *With Gross Test*	*(4)* *Allow Different Effects for AFDC and Medicaid*	*(5)* *Different Effects with Gross Test*
GAIN%	–0.519	–0.564	–0.117		
	(0.154)	(0.124)	(0.089)		
		[–0.192]	[–0.040]		
MED*				–0.347	–0.046
				(0.127)	(0.092)
				[–0.118]	[–0.016]
AFDC%				1.627	0.446
				(0.163)	(0.133)
				[0.552]	[0.152]
χ^2 Test				105.83	11.20
(p-value)				(0.000)	(0.001)

[a]Standard errors in parentheses except where noted; marginal effects at the means in brackets.
[b]Regressions include all variables listed in Table 2.
[c]MED* and AFDC% are measured as fractions in this table and all following tables.
[d]The χ^2 test is of the hypothesis that the coefficients on MED* and AFDC% have equal and opposite signs, the restriction implicit in the use of GAIN%.
Source: Sample composed of single mothers ages 18–55 with a child under 15 from the 1989–92 March Current Population Surveys.

nificant in either case. Including the gross test reduces the imputed AFDC maximum income level because the gross test is binding when income after disregards is relatively high. This tends to occur when there are many children in the family, since the childcare disregard is the primary reason that income after disregards may be high. The fact that including the gross test in the AFDC calculation reduces the magnitude of the effect of GAIN% suggests that AFDC income levels are indeed playing an important role in determining the effect of GAIN%.

We consider this hypothesis directly in columns (4) and (5) by allowing AFDC maximum income levels and Medicaid maximum income levels (AFDC% and MED*, respectively) to have separate effects. We then test the restriction implied by the use of GAIN% that the effects are equal and of opposite sign. For comparison, column (4) shows the results without including the gross test, while column (5) gives the (more appropriate) results with the gross test included. For both labor force participation and AFDC participation the estimated effect of AFDC is substantially larger in absolute value than the estimated Medicaid effect, and we easily reject the null hypothesis that the coefficients are equal in absolute value with opposite signs. While the estimated Medicaid effect is marginally statistically significant when the gross test is not included, it becomes much smaller and statistically insignificant when the gross test is included. The AFDC effect also becomes smaller when we impose the gross test, although it remains statistically significant. The marginal effects, which are calculated as the derivative of the normal cumulative density evaluated at the means of the data, are –0.11 for labor force participation and 0.15 for AFDC participation. The magnitude of these effects indicates that a one percentage-point increase in the AFDC income limit as a percentage of the poverty line yields a decrease of 0.0011 in the probability of labor force participation at mean values. This increase in the AFDC income limit would also cause a 0.0015 increase in the probability of AFDC participation at the mean values. For comparison, the predicted probability of labor force participation evaluated at the mean values of the explanatory variables is 0.73, and the predicted probability of AFDC participation at the means is 0.28.

Yelowitz found that including state-year interactions to control for the possibility of state-specific trends increased the absolute value of the coefficient on GAIN% in both the labor force and AFDC participation equations. We consider this modification in Table 4. Comparing column (2) in this table with column (5) of Table 3, we see that when we include these interactions in the more appropriate specification that allows the Medicaid and AFDC income limits (incorporating the gross test) to have separate effects, the Medicaid coefficients continue to be insignificantly different from 0. We easily reject the null hypothesis that the Medicaid and AFDC coefficients are equal in magnitude but opposite in sign.

The rest of Table 4 shows the results obtained when the sample of single mothers is split into women who were ever married and women who were never married. When GAIN% is used, only ever married women show statistically significant effects, which Yelowitz attributed to a greater responsiveness to Medicaid expansions among ever married women. However, when AFDC and Medicaid are allowed to have separate effects and the gross test is used, we find no evidence of responsiveness to Medicaid for either group. The Medicaid coefficients are close to 0 for both groups in the AFDC participation equation and are again statistically insignificant. The only sign of a possible Medicaid effect in the predicted direction is in the labor force participation equation for ever married women (column 4, top panel), but the effect is so imprecisely estimated that it is not statistically distinguishable from 0. The importance of the AFDC income limits seen in the whole sample is confirmed for both groups of women (columns 4 and 6, both panels).

Extensions

Having estimated unconstrained versions of Yelowitz's model on all of the subsamples he used in his paper, we find little evidence of an effect of the Medicaid expansions on either work or welfare participation. However, it is possible that an effect of the expansions exists, but that our efforts to estimate it are hampered by statistical imprecision. Consequently, we estimate our models using more years of the March CPS, from 1988 to 1996. In addition to adding more data, these additional years have the

Table 4. Alternative Samples and Specifications of Medicaid and AFDC in Probit Models with State-Year Interactions, 1989–92 March Current Population Surveys.[a]

Panel A: Models of Labor Force Participation[b]

Sample:	(1) All Women	(2)	(3) Ever Married Women	(4)	(5) Never Married Women	(6)
Variable	*Yelowitz Table IV, Col. (2)*	*Different Effects with Gross Test*	*Yelowitz Table VI, Col. (1)*	*Different Effects with Gross Test*	*Yelowitz Table VI, Col. (2)*	*Different Effects with Gross Test*
GAIN%	0.473 (0.168)		1.020 (0.248)		–0.024 (0.257)	
MED*		–0.017 (0.101) [–0.006]		0.186 (0.155) [0.051]		–0.185 (0.146) [–0.072]
AFDC%		–0.723 (0.169) [–0.240]		–0.752 (0.232) [–0.205]		–0.736 (0.269) [–0.287]
χ^2 Test 1[c] (p-value)		21.02 (0.000)		7.09 (0.008)		12.05 (0.001)
χ^2 Test 2[d] (p-value)		148.94 (0.509)		324.20 (0.000)		336.20 (0.000)

Panel B: Models of AFDC Participation

Sample:	(1) All Women	(2)	(3) Ever Married Women	(4)	(5) Never Married Women	(6)
	Yelowitz Table IV, Col. (4)	*Different Effects with Gross Test*	*Yelowitz Table VI, Col. (3)*	*Different Effects with Gross Test*	*Yelowitz Table VI, Col. (4)*	*Different Effects with Gross Test*
GAIN%	–0.649 (0.171)		–0.995 (0.254)		–0.354 (0.259)	
MED*		–0.022 (0.102) [–0.007]		–0.015 (0.155) [–0.004]		–0.026 (0.147) [–0.010]
AFDC%		0.875 (0.171) [0.296]		0.900 (0.235) [0.250]		0.901 (0.272) [0.355]
χ^2 Test 1 (p-value)		27.56 (0.000)		16.92 (0.000)		10.62 (0.001)
χ^2 Test 2 (p-value)		173.27 (0.0938)		225.15 (0.000)		228.87 (0.000)

[a]Standard errors in parentheses except where noted; marginal effects at the means in brackets.
[b]Regressions include all variables listed in Table 2, plus state-year interactions.
[c]The first χ^2 test is of the hypothesis that the coefficients on MED* and AFDC % have equal and opposite signs, the restriction implicit in the use of GAIN%.
[d]The second χ^2 test is of the hypothesis that the state-year interactions are jointly equal to zero.
Source: The sample is composed of single mothers ages 18–55 with a child under 15 from the 1989–92 March Current Population Surveys.

advantage that by the end of the period the expansions were fully implemented. This is particularly important in the case of OBRA 1990, which was one of the broadest expansions and which was only in effect for the last half of the last year of Yelowitz's sample.

Results from a model using Yelowitz's version of GAIN% that does not incorporate

Table 5. Probit Models Using the Full 1988–1996 CPS Sample: Alternative Samples and Specifications of Medicaid and AFDC.[a]

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Sample:	*All Women*		*All Women*		*Ever Married*		*Never Married*	
Variable	*Gain% w/o Gross Test*	*Different Effects with Gross Test*	*Gain% w/o Gross Test*	*Different Effects with Gross Test*	*Gain% w/o Gross Test*	*Different Effects with Gross Test*	*Gain% w/o Gross Test*	*Different Effects with Gross Test*
Panel A: Models of Labor Force Participation[b]								
Gain%	0.203		0.402		0.551		0.276	
	(0.048)		(0.064)		(0.098)		(0.090)	
	[0.069]		[0.135]		[0.153]		[0.108]	
Med*		–0.009		0.028		0.131		–0.060
		(0.040)		(0.058)		(0.087)		(0.084)
		[–0.003]		[0.009]		[0.036]		[–0.024]
AFDC%		–0.399		–0.681		–0.777		–0.606
		(0.070)		(0.104)		(0.143)		(0.162)
		[–0.134]		[–0.228]		[–0.216]		[–0.236]
χ^2 Test 1[c]		33.82		38.86		21.24		15.86
(p-value)		(0.000)		(0.000)		(0.000)		(0.000)
State*Year?	No	No	Yes	Yes	Yes	Yes	Yes	Yes
χ^2 Test 1[d]			464.65	450.79	559.75	601.39	731.80	684.38
(p-value)			(0.014)	(0.040)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Models of AFDC Participation								
Gain%	–0.194		–0.370		–0.547		–0.244	
	(0.048)		(0.064)		(0.099)		(0.090)	
	[–0.067]		[–0.126]		[–0.154]		[–0.096]	
Med*		0.046		0.030		–0.006		0.072
		(0.040)		(0.058)		(0.087)		(0.084)
		[0.016]		[0.010]		[–0.002]		[0.028]
AFDC%		0.512		0.841		0.939		0.854
		(0.070)		(0.105)		(0.146)		(0.162)
		[0.175]		[0.286]		[0.264]		[0.336]
χ^2 Test 1		64.34		68.49		43.36		30.54
(p-value)		(0.000)		(0.000)		(0.000)		(0.000)
State*Year?	No	No	Yes	Yes	Yes	Yes	Yes	Yes
χ^2 Test 2			483.40	472.83	506.64	485.05	562.81	573.92
(p-value)			0.002	0.006	0.000	0.002	0.000	0.000

[a]Standard errors in parentheses except where noted; marginal effects at the means in brackets.
[b]Regressions include all variables listed in Table 2.
[c]The first χ^2 test is of the hypothesis that the coefficients on Med* and AFDC% have equal and opposite signs, the restriction implicit in the use of Gain%.
[d]The second χ^2 test is of the hypothesis that the state-year interactions are jointly equal to zero.
Source: The sample is composed of single mothers ages 18–55 with a child under 15 from the 1988–1996 March Current Population Surveys.

the gross test and the unrestricted specification that incorporates the gross test (including Med* and AFDC% separately) for 1998–96 are presented in Table 5. Columns (1) and (2) show the results for all women when state-year interactions are not used. Columns (3)–(8) present the results when state-year dummies are included for all women, ever married women, and never married women, respectively. The top panel shows the results for labor force participation models, while the bottom panel shows the results for AFDC participation models.[16] In all cases we continue to reject the

[16]As in earlier tables, in the interest of space only the main coefficients of interest are shown. There is little change in the other estimated coefficients from those estimated for 1989–92.

Table 6. Comparison of Unweighted and Weighted Probit Models.[a]

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
	1989–92 CPS				*1988–96 CPS*			
Variable	*Unweighted*	*Weighted*[c]	*Unweighted*	*Weighted*	*Unweighted*	*Weighted*	*Unweighted*	*Weighted*
Panel A: Models of Labor Force Participation, All Women[b]								
Med*	0.058	0.190	–0.017	0.090	–0.009	0.028	0.028	0.080
	(0.091)	(0.091)	(0.101)	(0.102)	(0.040)	(0.041)	(0.058)	(0.060)
	[0.019]	[0.063]	[–0.006]	[0.030]	[–0.003]	[0.009]	[0.009]	[0.027]
AFDC%	–0.322	–0.434	–0.723	–0.790	–0.399	–0.458	–0.681	–0.737
	(0.132)	(0.133)	(0.169)	(0.171)	(0.070)	(0.073)	(0.104)	(0.106)
	[–0.107]	[–0.143]	[–0.240]	[–0.260]	[–0.134]	[–0.153]	[–0.228]	[–0.244]
χ^2 Test 1[d]	4.87	4.02	21.02	18.15	33.82	34.79	38.86	37.38
(p-value)	(0.027)	(0.045)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
State*year?	No	No	Yes	Yes	No	No	Yes	Yes
χ^2 Test 2[e]			148.94	145.03			450.79	446.04
(p-value)			(0.509)	(0.599)			(0.040)	(0.056)
Panel B: Models of AFDC Participation, All Women								
Med*	–0.046	–0.125	–0.022	–0.064	0.046	0.034	0.030	0.013
	(0.092)	(0.091)	(0.102)	(0.102)	(0.040)	(0.041)	(0.058)	(0.060)
	[–0.016]	[–0.042]	[–0.007]	[–0.022]	[0.016]	[0.012]	[0.010]	[0.004]
AFDC%	0.446	0.527	0.875	0.854	0.512	0.510	0.841	0.853
	(0.133)	(0.135)	(0.171)	(0.173)	(0.070)	(0.073)	(0.105)	(0.107)
	[0.152]	[0.178]	[0.296]	[0.288]	[0.175]	[0.173]	[0.286]	[0.289]
χ^2 Test 1	11.20	10.78	27.56	22.69	64.34	55.76	68.49	63.90
(p-value)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
State*year?	No	No	Yes	Yes	No	No	Yes	Yes
χ^2 Test 2			173.27	154.07			472.83	442.00
(p-value)			(0.094)	(0.393)			(0.006)	(0.068)

[a]Standard errors in parentheses except where noted, marginal effects at the means in brackets.
[b]Regressions include all variables listed in Table 2.
[c]Weights are CPS March supplement weights.
[d]The first χ^2 test is of the hypothesis that the coefficients on Med* and AFDC% have equal and opposite signs, the restriction implicit in the use of Gain%.
[e]The second χ^2 test is of the hypothesis that the state-year interactions are jointly equal to zero.
Source: Sample composed of single mothers ages 18–55 with a child under 15 from the 1989–92 or 1988–96 March Current Population Surveys.

restriction that the coefficients on AFDC% and Med* are equal in absolute value with opposite signs. As expected, the standard errors are roughly half as large when the full sample is used. Nevertheless, we do not find a statistically significant effect of Medicaid in any subsample or specification. The estimated coefficients on the AFDC income limits are quite similar to those for the 1989–92 sample, indicating a relatively stable relationship between AFDC financial incentives and labor force and welfare participation over time. (The marginal effects are –0.13 for labor force participation, as compared to –0.11, and 0.18 for AFDC participation, as compared to 0.15.)

Our second extension is to re-estimate the models not rejected by the data (that is, the models entering the Medicaid and AFDC income limits separately) using the CPS March Supplement weights. This serves as an informal specification test, since if the model is correctly specified, weighting should not substantively affect the probit coefficients.[17] We present these results in

[17]We would expect the weighted estimates to be inefficient, and it is interesting to note that in most cases the standard errors of the weighted estimates

Table 6 for both labor force participation (top panel) and AFDC participation (bottom panel). The odd-numbered columns show the unweighted estimates (reproduced from earlier tables for ease of comparison) and the even-numbered columns show the corresponding weighted estimates. The coefficients on the AFDC income limits are reassuringly similar across weighted and unweighted specifications, particularly for the AFDC participation models in both samples. The coefficients on the AFDC income limits in the labor force participation models vary slightly more, though again they are very similar in the whole sample.

In the AFDC participation models the Medicaid coefficients are also relatively stable (given the standard errors) between weighted and unweighted specifications, though they are not stable over time, with any hint of an effect of Medicaid disappearing when the entire sample is used. For the labor force participation models the Medicaid coefficients are less stable across weighted and unweighted specifications, even showing a statistically significant effect (at the 5% level) for the model omitting state-year interactions in the early sample. However, that effect disappears when the entire sample is used. Thus only one of the sixteen Medicaid coefficients in Table 6 is statistically significant. A comparison of the results between the weighted and unweighted estimates in Table 6 does raise the possibility that the model is misspecified with respect to the Medicaid parameter. Since the CPS weights are designed to adjust for the relative oversampling of individuals in small states, one interpretation of our results is that the effect of Medicaid on labor force participation may differ by state. In this case, the coefficients in the weighted regressions provide an average of the underlying varying treatment effects different from that yielded by the unweighted estimates.

Our final extension is to consider a model of labor supply, rather than labor force participation. It is possible that women adjust their hours of work in response to the Medicaid expansions, even though we find no evidence of a participation effect. Since hours of work are censored at 0 for nonworkers, we estimate a Heckman selection-corrected model assuming that education and age squared do not affect hours of work conditional on the wage. Since the wage is also unobserved for nonworkers, we estimate three equations: a participation equation to obtain the inverse Mills ratio, a wage equation to obtain the predicted wage, and the hours equation. We find that the Medicaid income limits are unrelated to hours of work.[18]

Conclusions

There has been a strong interest in designing policies that help single-headed families leave cash assistance for many years, and the replacement of AFDC by TANF has accentuated this interest. Based on economic theory and the empirical work of Yelowitz (1995), it appeared that the Medicaid expansions would decrease participation in cash assistance by breaking the link between AFDC and Medicaid for children. In this paper we re-examine the evidence from the CPS found in the Yelowitz study.

We conclude that there is no evidence detectable in the CPS data of a negative relationship between welfare participation and increases in the Medicaid income limits. Nor is there evidence that the Medicaid

are equal to or greater than the respective standard errors for the unweighted estimates. It would also be possible to test formally the equality of the weighted and unweighted estimates using a Hausman test, but we have not pursued this.

[18]In the interest of space we do not show our results here, but they are available upon request. Our standard errors reflect the heteroskedasticity caused by the censoring, but do not account for the fact that the probit coefficients are estimated. Note that the simpler tobit model of hours worked is less informative, since if the tobit model is correctly specified, we would expect the probit model of labor force participation and the tobit model to produce the same coefficients up to a factor of proportionality.

expansions increased labor force participation. We find that Yelowitz's results were the result of two factors. First, he imposed a strong restriction on the parameter estimates that is not predicted by theory and is rejected in the CPS data. This restriction has the effect of attributing the effect of any decreases in AFDC generosity to the Medicaid expansions. Second, he incorrectly calculated the AFDC break-even income by ignoring the gross test, resulting in higher imputed AFDC break-even income levels for larger families. Once these problems are addressed, the Medicaid income limits have no statistically significant effect on AFDC or labor force participation. These results are robust with respect to the inclusion of state-year interactions, splitting the sample between never married women and ever married women, and adding five more years of data. The AFDC income limits, however, are statistically significantly related to welfare and labor force participation in all specifications and samples, and are stable across specifications.

The importance of the AFDC income limits is not surprising in light of the theoretical results above. The lack of a Medicaid effect is somewhat surprising, as the theory shows that it is plausible for a woman to respond to the Medicaid expansions by moving from welfare to work. However, if α (the value the individual places on Medicaid) is less than one, the "notch" in the budget constraint is much smaller. This could occur if individuals were able to receive care even without Medicaid (such as emergency room or clinic care), if they tended not to use health care services, or if few physicians in an individual's vicinity accepted Medicaid as payment. Even if $\alpha = 1$, Figure 1 overstates the value of the Medicaid expansions to the family, since AFDC provides cash assistance and Medicaid for the mother herself as well as all of her children, but the mother and any older children would not be eligible for coverage under the expansions. This implies that the value of Medicaid coverage under the expansions may be relatively small. In that case, the number of women moving to a tangency at a point such as J in Figure 1 as a result of the expansions may be too small for us to detect a Medicaid effect in the data.[19] As our coefficients are not precisely zero, we cannot rule out a small effect of Medicaid on work and welfare behavior, but we are able to rule out large effects such as those suggested by Yelowitz's results. Our finding of little to no effect of the Medicaid expansions on work and welfare participation is consistent both with our results using dynamic models of labor force participation in the SIPP (Ham and Shore-Sheppard 2001) and with other work on the expansions that has found that they had a much smaller impact on insurance coverage than would be predicted given the magnitude of the eligibility increases (see, for example, Ham and Shore-Sheppard 2005; Card and Shore-Sheppard 2004).

[19]One might argue that the Medicaid coefficient is being biased in absolute value because we omit wages in the equation and wages for low-income workers are falling over this period while the Medicaid income limits are rising. However, our most general specification contains state dummies interacted with time dummies, which will capture much of the movement in wages.

REFERENCES

Ashenfelter, Orley. 1983. "Determining Participation in Income-Tested Social Programs." *Journal of the American Statistical Association,* Vol. 78, No. 383, pp. 517–25.

Blank, Rebecca M. 1989. "The Effect of Medical Need and Medicaid on AFDC Participation." *Journal of Human Resources,* Vol. 24, No. 1 (Winter), pp. 54–87.

Card, David, and Lara Shore-Sheppard. 2004. "Using Discontinuous Eligibility Rules to Identify the Effects of the Federal Medicaid Expansions on Low Income Children." *Review of Economics and Statistics,* Vol. 86, No. 3 (August), pp. 752–66.

Cutler, David, and Jonathan Gruber. 1996. "Does Public Insurance Crowd out Private Insurance?" *Quarterly Journal of Economics,* Vol. 111, No. 2 (May), pp. 391–430.

Ham, John C., and Lara D. Shore-Sheppard. 2001. "The Impact of Public Health Insurance on Employment Transitions." Unpublished paper, Ohio State University.

____. 2003. "Did Expanding Medicaid Affect Welfare Participation?" National Bureau of Economic Research Working Paper No. 9803.

____. 2004. "The Effect of Medicaid Expansions for Low-Income Children on Medicaid Participation and Private Insurance Coverage: Evidence from the SIPP." *Journal of Public Economics,* Vol. 89, No. 1 (January), pp. 57–83.

Meyer, Bruce D., and Dan T. Rosenbaum. 2001. "Welfare, the Earned Income Tax Credit, and the Employment of Single Mothers." *Quarterly Journal of Economics,* Vol. 116, No. 3 (August), pp. 1063–1114.

Moffitt, Robert, and Barbara Wolfe. 1992. "The Effect of the Medicaid Program on Welfare Participation and Labor Supply." *Review of Economics and Statistics,* Vol. 74, No. 4 (November), pp. 615–26.

Shore-Sheppard, Lara. 2003. "Expanding Public Health Insurance for Children: Medicaid and the State Children's Health Insurance Program." In Rachel A. Gordon and Herbert J. Walberg, eds., *Changing Welfare.* New York: Kluwer Academic, pp. 95–117.

U.S. House of Representatives Committee on Ways and Means. 1987–2000. *Green Book: Background Material and Data on Programs within the Jurisdiction of the Committee on Ways and Means.* Washington, D.C.: Government Printing Office.

Winkler, Anne. 1991. "The Incentive Effects of Medicaid on Women's Labor Supply." *Journal of Human Resources,* Vol. 26, No. 2 (Spring), pp. 308–37.

Yelowitz, Aaron. 1995. "The Medicaid Notch, Labor Supply, and Welfare Participation: Evidence from Eligibility Expansions." *Quarterly Journal of Economics,* Vol. 110, No. 4 (November), pp. 909–40.