The Invisible Safety Net: How Benefit Continuations Under Means-Tested Transfer Programs Mitigate Estimated Effective Marginal Tax Rates

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Conference Draft: Please Do Not Cite Without Permission

Abstract

Researchers have long observed that the simultaneous phaseout of benefits under multiple means-tested transfer and tax programs as household income increases can result in shockingly high effective marginal tax rates (EMTRs) for some low- and moderate-income households. However, those observations have been based on static calculations or simulations or on analyses of cross-sectional data and thus do not reflect the dynamics of actual income and benefit changes. Although tax benefits adjust immediately to household income changes, transfer benefits do not. For example, under program laws and regulations, a household's benefits may be unaffected by an income increase for at least 12 months under Medicaid, the Children's Health Insurance Program (CHIP), and the National School Lunch Program (NSLP), and for at least 6 months under the Supplemental Nutrition Assistance Program (SNAP).

We address this gap in the literature by using full panel data from the 2008 Survey of Income and Program Participation to estimate the dynamics of income and benefit changes under these programs. Our sample includes 416,124 month observations from 14,756 low- and moderate-income households that had no elderly or disabled members and that did not change in size, composition, or state of residence. We use three-level, mixed-effects regression models with random intercepts at the state and household levels and with cluster robust standard errors at the state level in our analyses.

We first examine whether benefits continue to be affected by prior incomes for as long as the program rules permit. For this analysis, we include all households with earned incomes below the applicable income thresholds for the programs. We find that these households continue to receive significantly higher benefits after an earned income increase for 19 months under Medicaid/CHIP, 15 months under SNAP, and 11 months under NSLP and related school nutrition programs, after controlling for the applicable poverty line and for household earned income in each subsequent month.

We then consider how these benefit continuations affect the high EMTRs often associated with benefit phaseouts. We concentrate this analysis on households that are typically thought to face the highest EMTRs: unmarried households with children and earned incomes between 50 percent and 150 percent of the applicable poverty line. Overall, for each dollar increase in their monthly earned incomes, these households receive total additional benefits under these programs of $0.34 over the next six months, after controlling for the applicable poverty line and for household earned income in each subsequent month. These benefit continuations reduce the estimated EMTR for these households under these programs by an average of 57 percent during the first six months after an earned income increase in a dynamic analysis, as compared with the estimate from a static analysis. If similar results apply to other means-tested transfer programs, the combined benefit continuations could offset about 40 percent of the estimated EMTRs for these households during the first six months after an earned income increase.

The Invisible Safety Net: How Benefit Continuations

Under Means-Tested Transfer Programs Mitigate Estimated Effective Marginal Tax Rates

As low- and moderate-income households earn additional income, the benefits that they receive under multiple means-tested transfer and tax programs may be simultaneously reduced or eliminated. These benefit reductions, combined with federal and state income taxes and payroll taxes on the additional earned income, can result in shockingly high effective marginal tax rates (EMTRs) for these households – a household may realize very little increase in its disposable income for each dollar increase in its earned income. As a result, these households may have reduced incentives to earn additional income and the inequality-reducing effects of these programs may be diminished.

Because low- and moderate-income households with children receive the most benefits under means-tested transfer and tax programs, they typically face the highest EMTRs. Even for these households, estimates of the EMTRs vary widely, depending on the analytical method, the state, the tax and transfer programs included, the household's specific income level, and the size of the income increase (Holt & Romich, 2007; Leguizamon, 2012). However, the estimates often approach or exceed 100 percent for some low- and moderate-income households with children (Acs, Coe, Watson, & Lerman, 1998; Maag, Steuerle, Chakravarti, & Quakenbush, 2012; Wolfe, 2002). The Congressional Budget Office's analysis (2012b, 2012c) with taxes and three large transfer programs (the Supplemental Nutrition Assistance Program (SNAP), Temporary Assistance for Needy Families (TANF), and the Housing Choice Voucher Program (Housing Vouchers)) estimated that EMTRs average about 80 percent for single-parent households in Pennsylvania with one child and incomes between 50 percent and 150 percent of the poverty line, which is comparable to our own estimates for these households in Illinois with taxes and all major means-tested transfer programs (Reinbold, 2013).

However, prior estimates of these EMTRs (including our own) have typically been derived from static calculations or simulations or from analyses of cross-sectional data. This limitation is not concerning with respect to the tax programs, because benefits under those programs adjust immediately to income changes – the household may not realize the change in benefits until the following year's tax payment or refund, but the calculation of those benefits is retroactive to the income change. To the contrary, however, benefits under most means-tested transfer programs do not adjust immediately to income changes (Romich, 2006). The household typically is not even required to report the income change to the administrative agency for a period of time and, even after that reporting, the agency may not immediately adjust the household's benefits.

For example, a household's income increase may not affect its Medicaid coverage for more than 12 months. Absent a reported change, states are not required to redetermine the eligibility of Medicaid beneficiaries for up to 12 months (42 C.F.R. § 435.916(a)). States are required to have procedures to ensure that beneficiaries "promptly" report income changes and other changes that may affect their Medicaid eligibility (42 C.F.R. § 435.916(b)), which typically means within 10 days after the end of the month in which the change occurred. However, after receiving those reports, states must continue to provide benefits to families with children for at least 6 months (42 U.S.C. § 1396r-6(a)(1)(A)) and may continue to provide those benefits for as long as 12 months (42 U.S.C. § 1396r-6(a)(5)). The same rules apply to the Children's Health Insurance Program (CHIP) (42 C.F.R. § 457.343).

Similarly, an income increase may not affect a household's SNAP benefits for more than 6 months. States may certify households to be eligible for SNAP for as long as 12 months (42 C.F.R. § 273.10(f)), although households certified for longer than 6 months must submit periodic reports at least every 6 months (42 C.F.R. § 273.12(a)(5)(iii)(A)). In some states, households are not required to report income changes between periodic reports unless their new income exceeds the gross income limit for receiving any benefits (42 C.F.R. § 273.12(a)(5)(iii)(E); 42 C.F.R. § 273.12(a)(5)(v)). After receiving notice of an income change, states are required to make benefit changes effective no later than the following month (42 C.F.R. § 273.12(c)(2)(i)).

Finally, a household's income increase also may not affect its children's benefits under the National School Lunch Program (NSLP) for more than 12 months. Once children are determined to be eligible for the school year, that eligibility must remain in effect for the entire school year and for up to the first 30 days of the next school year (7 C.F.R. § 245.6(c)(1)). Households are not required to report income changes or other changes in circumstances that occur during the school year, until they apply for benefits for the following school year (7 C.F.R. § 245.6(c)(3)).

Because of these program rules, one would expect that a household that experiences an income increase in a particular month might continue to receive significantly greater benefits under these programs for at least 6 to 12 months, as compared with similar households that were already at the new income level and did not experience an income increase. Indeed, given possible reporting and processing delays, one might expect these benefit continuations to persist even longer. Therefore, a static analysis might overestimate the benefits lost by a household in response to an income increase by assuming that all similar households at the same income level are eligible for the same benefits, without considering their income histories.

In order to estimate the dynamic effects of income increases on program benefits, we need panel data on program benefits and incomes for households over time. The Survey of Income and Program Participation (SIPP) provides just such data for several means-tested transfer programs, albeit with certain well-known limitations. In this paper, we use full panel data from the 2008 SIPP to estimate the dynamics of income and benefit changes under the programs described above: Medicaid and CHIP, which we analyze together and refer to as MEDICHIP; SNAP; and NSLP and related school breakfast and summer food programs, which we analyze together and refer to collectively as School Nutrition programs.

We pursue two objectives in this paper. First, we want to determine whether households that experience an earned income increase continue to receive significantly higher benefits under these programs than similar households that were already at the new income level and, if so, for how long those benefit continuations persist. Second, if those benefit continuations do occur, we want to determine the extent to which they may mitigate the high EMTRs often associated with benefit phaseouts under these programs. For this second objective, we want to focus on households that are typically thought to face the highest EMTRs: unmarried households with children and earned incomes between 50 percent and 150 percent of the applicable poverty line.

Data

As stated above, we used full panel data from waves 1 through 12 of the 2008 SIPP. In each wave, we dropped households with any members that were 65 years old or older, that had Medicare coverage, or that received Supplemental Security Income or employer disability benefits, because households with elderly or disabled members have access to those programs and other transfer programs that may affect benefits under the programs studied. After combining the waves, we dropped households that changed in size, composition, or state of residence during the survey, because those changes may also affect benefits under the programs studied. Finally, because our analysis is at the household level, we dropped observations for all people in the household other than the household head, so we had only one series of month observations per household.

Table 1 presents the sample characteristics for the households in our analysis samples. As described above, we pursued two objectives: determining for how long households that experience an earned income increase continue to receive significantly higher benefits than similar households that were already at the new income level; and determining the extent to which those benefit continuations may mitigate the high EMTRs often associated with benefit phaseouts. For the first objective, we considered all households with earned incomes below the eligibility limits for MEDICHIP, SNAP, or School Nutrition programs in at least one month. For the second objective, we considered only unmarried households with children and earned incomes between 50 percent and 150 percent of the applicable poverty line in at least one month. Table 1 shows descriptive data for each of these samples.

Table 1

Sample Characteristics

Variable	All households with earned incomes below program eligibility limit in at least one month (N = 416,124 observations; 14,756 households)			Unmarried households with children and earned incomes between 50% and 150% of FPL in at least one month (N = 28,536 observations; 939 households)		
	Mean	SD	%	Mean	SD	%
Household earned income for month	$4,621.62	$5,130.94		$2,002.34	$2,078.86	
Household poverty line for month	$1,417.17	$457.03		$1,626.02	$379.75	
Number of children in household in month	0.74	1.10		1.70	1.01	
Type of public health insurance for household in month:						
None			89.24			46.36
Medicaid only			8.89			45.99
CHIP only			1.79			7.04
Medicaid and CHIP			0.08			0.62
Value of MEDICHIP coverage for household in month	$41.89	$148.82		$205.66	$269.97	
Household received SNAP benefits in month:						
No			92.34			63.39
Yes			7.66			36.61
Amount of SNAP benefits received by household in month	$25.09	$105.15		$129.95	$204.43	
Type of school lunch received by household children in month:						
None or regular price			87.66			41.16
Reduced price			2.56			8.63
Free			9.78			50.21
Type of school breakfast received by household children in month:						
None or regular price			91.57			56.67
Reduced price			0.93			3.63
Free			7.50			39.70
Value of School Nutrition benefits received by household in month	$17.16	$53.60		$79.15	$88.82	
Head of household’s sex:						
Male			46.63			17.80
Female			53.37			82.20
Head of household’s race:						
White			80.06			62.05
Black			12.31			30.12
Asian			4.32			2.57
Other			3.31			5.26
Head of household is Spanish, Hispanic or Latino:						
No			90.30			77.95
Yes			9.70			22.05
Head of household was born in U.S.:						
No			14.04			18.53
Yes			85.96			81.47
Head of household’s years of education	13.64	2.68		12.35	2.66	

Household poverty line is the poverty line computed by the Census Bureau based on the household’s size, composition, and state of residence, as included in the SIPP data. We calculated *value of MEDICHIP coverage* using the person market value of Medicaid values included in the Census Bureau’s Current Population Survey (CPS) data, separately by state, year, and age group. For persons 21 years old or younger, we used the most common value in the CPS data for the state, year, and age group – it was always the case that a large majority of observations had the same value. For persons older than 21 years, we used the lowest value in the CPS data for the state, year, and age group – the values were typically more widely distributed for these individuals so we chose the lowest values so that our benefit estimates would be conservative. We then summed the values for each month for all persons in the household. We calculated *value of School Nutrition benefits* using the U.S. Department of Agriculture's reimbursement rates for school lunch and breakfast programs, separately by state, year, and free or reduced-price meal status. We then multiplied the applicable daily rate for each household by 20 days per month and by the number of children in the household receiving each program. All of the other variables were reported by the households in the SIPP data.

It is well-known that households often underreport the benefits that they receive under transfer programs in the SIPP and similar surveys (Moffitt & Scholz, 2010; Ratcliffe, McKernan, & Finegold, 2008). Researchers sometimes gross up or reimpute these benefits to approximate administrative totals more closely. Because our primary goal is estimating changes in benefits received by households after income increases and not the static receipt of benefits by households across income levels, we do not use those approaches here. As long as households are not systematically underreporting benefits prior to income increases as compared with their reporting after those increases, this issue should not affect our results. Indeed, if anything, we might expect households to instead underreport benefits to a greater extent after their income increases above program limits, which would cause our estimates below to be conservative. We discuss this issue more below.

The valuation of MEDICHIP benefits has also been the subject of much discussion. The Census Bureau does not provide any measures for those values in the SIPP data, but it provides two different measures for those values in the CPS data: the market value and the fungible value. The Census Bureau estimates the market value for MEDICHIP based on government expenditures for the program by state and risk class. The Census Bureau also calculates a fungible value for MEDICHIP, under an assumption that households would spend money on medical expenses only after they satisfy their basic needs for food and housing. For households with insufficient income to satisfy those basic needs, the fungible value of MEDICHIP is set at zero. For households with income above that standard, the fungible value is set at the amount of the household's income above that standard, up to the market value (CBO, 2012a). In addition to these CPS values, other researchers have valued MEDICHIP benefits at the cost of a typical HMO policy (Moffitt & Scholz, 2010).

We use the CPS market value of MEDICHIP benefits in all of our analyses. Using the fungible value instead might overstate our results, because the fungible value of MEDICHIP coverage for low-income households increases as their income increases. Therefore, with the fungible value, it might appear that these households are receiving greater MEDICHIP benefits as their income increases, when in fact they are merely maintaining their existing coverage. It is true that the CPS market value may overestimate the value of coverage to households, because it includes administrative costs. However, as long as the measure is applied consistently before and after household income increases, this issue should have little effect on our results. A larger issue may be the fact that we are not including premiums and copayments required under MEDICHIP in our analysis. These fees are limited to five percent of household income and are typically much smaller than that, especially for children (Heberlein, Brooks, Alker, Artiga, & Stephens, 2013). However, they do typically increase in steps as household income increases, so they can contribute to higher EMTRs (CBO, 2012b).

Another established issue with the SIPP relates to the structure of the survey. In the SIPP, the Census Bureau surveys households every four months and asks them to report their income and benefits in the current month and the three prior months. These four months are referred to as survey reference months and are numbered consecutively from one to four in each wave. Households are more likely to report changes in income and benefits between waves than within waves (Ratcliffe et al., 2008). To address this "seam bias," researchers typically either use only the data from the fourth month for each household from each wave (and thus use wave data rather than month data) or control for the survey reference month. Because we sought to estimate monthly changes in benefits, we could not drop the first three months for each household from each wave. Instead, we control for the survey reference month in all of our analyses.

Methods

We used panel data regressions to estimate (a) the persistence of the relationship between household earned income increases and benefits received under these programs, (b) the relationship between household earned income increases and the cumulative value of benefits received under these programs over subsequent periods of various lengths, and (c) the EMTRs under these programs over those periods. Our baseline model to estimate the persistence of the relationship between household earned income increases and benefits is as follows:

$$benefits_{h,t} = \alpha + \beta_1\left(inc_{h,2} - inc_{h,1}\right) + \beta_2 inc_{h,t} + \beta_3 inc_{h,t-1} + \cdots + \beta_t inc_{h,2} +$$

$$\beta_{t+1} povline_{h,t} + \beta_{t+2} refmonth_{h,t} + \gamma controls_{h,t} + \varepsilon_{h,t}.$$

Here, $benefits_{h,t}$ are the benefits received by the household under the program in the current month, which we regress on (a) the household's earned income change from the earliest month to the immediately following month, (b) the household's earned income during each month subsequent to the earliest month up to and including the current month, (c) the applicable poverty line in the current month, (d) the current SIPP survey reference month, and (e) certain demographic variables relating to the head of the household in the current month (sex, race, whether Spanish/Hispanic/Latino, whether born in the U.S., and years of education). Because we are interested in the relationship between household earned income increases and benefits received, we include only households whose earned income either increased or remained constant from the earliest month to the immediately following month; if we included households whose earned income decreased over that period, we would also be estimating the persistence of the relationship between household earned income decreases and benefits received, which we would expect to be quite different. Also, we include only households whose earned income during the earliest month was below the applicable income threshold for the program (130 percent of the poverty line for SNAP, 185 percent of the poverty line for School Nutrition programs, and state- and year-specific values ranging from 140 percent to 400 percent of the poverty line for MEDICHIP). The program income thresholds have varying income definitions that are typically broader than earned income, so we may be including some households that are above the program income thresholds, but that issue should, if anything, cause our estimates below to be conservative.

Our baseline model to estimate the relationship between household earned income increases and the cumulative value of benefits over various periods after an earned income increase is similar. We regress cumulative benefits over the period on the change in earned income, controlling for the household's earned income in each month after the change:

$$benefits_{h,t} + benefits_{h,t-1} + \cdots + benefits_{h,2} = \alpha + \beta_1\left(inc_{h,2} - inc_{h,1}\right) + \beta_2 inc_{h,t} + \beta_3 inc_{h,t-1} + \cdots + \beta_t inc_{h,2} + \beta_{t+1} povline_{h,t} + \beta_{t+2} refmonth_{h,t} + \gamma controls_{h,t} + \varepsilon_{h,t}.$$

And our baseline model to estimate the EMTRs under these programs over various periods after an earned income increase is similar, except that we regress average monthly benefits over the period on the change in earned income, with controls for the pre-change earned income and for household earned income changes in subsequent months:

$$(benefits_{h,t} + benefits_{h,t-1} + \cdots + benefits_{h,2})/(t-1) = \alpha + \beta_1\left(inc_{h,2} - inc_{h,1}\right) + \beta_2 inc_{h,1} + \beta_3(inc_{h,t} - inc_{h,t-1}) + \cdots + \beta_t(inc_{h,3} - inc_{h,2}) + \beta_{t+1} povline_{h,t} + \beta_{t+2} refmonth_{h,t} + \gamma controls_{h,t} + \varepsilon_{h,t}.$$

In these models, we again include only households whose earned income either increased or remained constant from the earliest month to the immediately following month. Also, for reasons explained above, we include only households (a) that were headed by a single person, (b) with at least one child younger than age 18, and (c) whose earned income during the earliest month was between 50 percent and 150 percent of the applicable poverty line.

We obtained estimates using several different panel data regression techniques that addressed our primary estimation concerns: correlation within households over time; correlation across households within states; oversampling of low-income households in the SIPP; and attrition of households from wave to wave in the SIPP. We estimated a variety of models with fixed effects at the household level, including models with cluster robust standard errors at the household level, models with cluster robust standard errors at the state level, models with bootstrapped standard errors, and models with sampling weights adjusted for household attrition. We also estimated a variety of models with random effects at the household level, including models with cluster robust standard errors at the household level, models with cluster robust standard errors at the state level, and models with bootstrapped standard errors. Finally, we estimated a variety of mixed-effects models, including models with random intercepts at the household level, models with random intercepts at both the state and household levels, models with cluster robust standard errors at the household level, models with cluster robust standard errors at the state level, and models with bootstrapped standard errors. The choice of models had little effect on the results, as the coefficients across all of these models followed the same patterns. Significance levels differed slightly across models depending on the error modeling, but those differences also had little effect on the results. The inclusion of sampling weights had very little effect on the results, which is likely due to the fact that all of our models control for income and most demographic factors that would be expected to affect sampling likelihood and attrition (Winship & Radbill, 1994).

Our preferred model for all of our analyses is a three-level, mixed-effects model with random intercepts at the state and household levels and with cluster robust standard errors at the state level. These models explicitly model the nested structure of the data (month observations within households within states) and address both correlation within households over time and correlation across households within states (Cameron & Trivedi, 2010; Rabe-Hesketh & Skrondal, 2012). And because we control for household earned income and demographic factors, they also effectively address the oversampling of low-income households and sample attrition. The same models with bootstrapped standard errors also accomplish these goals and produced very similar results, but required much more computational time.

Results

Our estimates of the persistence of the relationship between household earned income increases and benefits received under these programs are shown in Table 2. Each coefficient in the table derives from a separate regression. To be concise, we present only the single coefficient of interest and the sample size for each regression. Because MEDICHIP has the highest income thresholds, it has the largest sample size for each month, followed by School Nutrition programs and then by SNAP. We present results for the first 24 months after an earned income increase.

Table 2

Relationship between Prior Earned Income Increase and Value of Program Benefits in Current Month

Months Since Earned Income Increase	Program					
	MEDICHIP		SNAP		School Nutrition	
	β	Obs./HH	β	Obs./HH	β	Obs./HH
1	0.00841***	177,428/10,993	0.00891***	104,865/8,188	0.00135***	138,669/9,608
2	0.00814***	167,225/10,904	0.00845***	98,247/8,098	0.00135***	130,324/9,516
3	0.00781***	157,082/10,691	0.00808***	91,703/7,927	0.00125***	122,043/9,327
4	0.00699***	147,220/8,901	0.00734***	85,313/6,444	0.00103**	113,975/7,651
5	0.00655***	141,046/8,835	0.00679***	81,334/6,379	0.00090**	108,963/7,579
6	0.00616***	134,153/8,775	0.00596***	77,120/6,319	0.00077*	103,505/7,519
7	0.00582***	127,201/8,610	0.00547***	72,878/6,177	0.00087**	98,014/7,368
8	0.00504***	120,454/7,639	0.00520***	68,730/5,405	0.00084**	92,673/6,501
9	0.00477***	115,538/7,570	0.00420***	65,672/5,342	0.00072**	88,748/6,435
10	0.00463***	110,011/7,528	0.00381**	62,402/5,288	0.00056**	84,444/6,388
11	0.00447***	104,502/7,414	0.00300**	59,133/5,211	0.00040*	80,132/6,298
12	0.00431***	99,109/6,685	0.00262**	55,926/4,672	0.00030	75,931/5,654
13	0.00407***	94,832/6,620	0.00239**	53,345/4,601	0.00028	72,552/5,584
14	0.00365***	90,125/6,561	0.00246**	50,627/4,543	0.00039	68,905/5,529
15	0.00291***	85,409/6,474	0.00215*	47,888/4,474	0.00044	65,241/5,447
16	0.00230**	80,824/5,879	0.00169	45,220/4,050	0.00042	61,692/4,928
17	0.00246***	77,201/5,830	0.00152	43,030/3,996	0.00044	58,851/4,879
18	0.00210**	73,110/5,777	0.00083	40,682/3,948	0.00029	55,688/4,836
19	0.00176*	69,090/5,661	0.00032	38,368/3,861	0.00024	52,589/4,735
20	0.00093	65,211/5,129	-0.00025	36,155/3,464	0.00027	49,612/4,272
21	0.00103	62,158/5,088	-0.00072	34,385/3,423	0.00031	47,253/4,226
22	0.00124	58,685/5,038	-0.00072	32,463/3,385	0.00028	44,611/4,178
23	0.00122	55,268/4,959	-0.00031	30,553/3,328	0.00031	42,006/4,105
24	0.00100	51,890/4,448	-0.00013	28,654/2,962	0.00012	39,430/3,655

Note. Samples include only households (a) that had no elderly or disabled members; (b) that did not change in size, composition, or state of residence from the earliest month to the current month; (c) whose earned income increased or remained constant from the earliest month to the immediately subsequent month; and (d) whose earned income during the earliest month was below the applicable income threshold for the program. All models are maximum likelihood panel data regressions with random intercepts at the state and household levels; with robust standard errors to adjust for clustering at the state level; and with controls for the household's earned income during each month subsequent to the earliest month up to and including the current month, for the applicable poverty line during the current month, for the current SIPP survey reference month, and for certain demographic variables relating to the head of the household in the current month (sex, race, whether Spanish/Hispanic/Latino, whether born in the U.S., and years of education).

* $p < .10$. ** $p < .05$. *** $p < .01$.

The results for all three programs conform to expectations. An earned income increase is associated with significantly higher benefits at first under all three programs, and both the magnitude and the statistical significance of that relationship decrease over time. The relationship remains statistically significant for 19 months with MEDICHIP, for 15 months with SNAP, and for 11 months with School Nutrition programs. Beyond those periods, an earned income increase continues to be associated with higher benefits for all 24 months with MEDICHIP and with School Nutrition programs. With SNAP, that association is positive only for the first 19 months and then becomes negative, but that negative relationship is always quite small and statistically insignificant.

We see from Table 2 that static estimates are likely to overstate the benefits lost by households as their income increases. On average, a household that is under the income threshold for SNAP (and thus also under the income thresholds for MEDICHIP and School Nutrition programs) that experiences a $100 earned income increase in a month would be expected to receive about $1.87 more in benefits under those three programs in the following month than a similar household that was already at the new income level. And even 12 months after the earned income increase, the first household would still be expected to receive about $0.72 more in benefits than the second household. The total difference in benefits between the households over those 12 months would be expected to be about $15.33, or about 1.3 percent of the $1200 earned income increase over that period.

The results in Table 2 are, of course, averaged across households. One would not predict an individual household to receive $1.87 more in benefits in the month after a $100 income increase than another similar household that was already at the new income level. In particular, although the value of SNAP benefits reported in the SIPP are nearly continuous, the values of

MEDICHIP benefits and of School Nutrition program benefits (as we have calculated them) have only a few possible values for each household. Individual households would still experience the disposable income "cliffs" associated with losing benefits entirely under MEDICHIP or School Nutrition programs, but may not do so for a full year or longer after an income increase. So, when our results indicate that households are receiving more benefits under MEDICHIP, it means that they have an increased probability of receiving coverage under MEDICHIP for at least some household members. And when our results indicate that households are receiving more benefits under School Nutrition programs, it means that their children have an increased probability of receiving free meals versus reduced-price meals, or of receiving reduced-price meals versus full-price or no meals.

Also, it is not quite as simple as summing across programs in Table 2, because different households are included for each program. For consistency, we need to include the same households for each program. Thus, we also estimated the relationship between household earned income increases and the cumulative value of benefits received under these programs over various periods after an earned income increase for a common group of households. As explained above, we focused on households that are typically thought to face the highest EMTRs – unmarried households with children and earned incomes between 50 percent and 150 percent of the applicable poverty line.

Our estimates of the relationship between household earned income increases and the cumulative value of benefits received under these programs for these households are provided in Table 3. Again, each coefficient in the table derives from a separate regression and we present only the single coefficient of interest and the sample size for each regression. However, the sample sizes are now the same for each program, as we are including the same households.

Table 3

Relationship between Earned Income Increase and Value of Program Benefits over Subsequent Periods [and 95% Confidence Intervals]

Length of Period After Earned Income Increase	Program				Obs./HH
	MEDICHIP	SNAP	School Nutrition	Three Program Total	
6 months	0.150**	0.189***	0.023	0.343***	7,811/723
	[0.018, 0.282]	[0.066, 0.312]	[-0.023, 0.068]	[0.109, 0.576]	
12 months	0.188	0.286**	0.044	0.492*	5,812/530
	[-0.163, 0.539]	[0.054, 0.518]	[-0.037, 0.124]	[-0.024, 1.007]	
18 months	0.342	0.350**	0.053	0.715*	4,298/450
	[-0.265, 0.950]	[0.026, 0.674]	[-0.047, 0.153]	[-0.120, 1.550]	
24 months	0.381	0.409**	0.068	0.811*	3,082/343
	[-0.197, 0.959]	[0.009, 0.809]	[-0.053, 0.188]	[-0.018, 1.641]	

Note. Samples include only households (a) that had no elderly or disabled members; (b) that did not change in size, composition, or state of residence from the earliest month to the current month; (c) that were headed by a single person; (d) with at least one child younger than age 18; (e) whose earned income increased or remained constant from the earliest month to the immediately subsequent month; and (f) whose earned income during the earliest month was between 50 percent and 150 percent of the applicable poverty line. All models are maximum likelihood panel data regressions with random intercepts at the state and household levels; with robust standard errors to adjust for clustering at the state level; and with controls for the household's earned income during each month subsequent to the earliest month up to and including the current month, for the applicable poverty line during the current month, for the current SIPP survey reference month, and for certain demographic variables relating to the head of the household in the current month (sex, race, whether Spanish/Hispanic/Latino, whether born in the U.S., and years of education).

* $p < .10$. ** $p < .05$. *** $p < .01$.

Again, the results for all three programs are as expected. For these households, an earned income increase is associated with higher benefits in all periods after the increase and those additional benefits accumulate over time. That relationship is statistically significant only for SNAP and for the 6-month total for MEDICHIP, but it is consistent across all programs.

Considering the totals for all three programs, an unmarried household with children in this income range that experiences a $100 earned income increase in a month would be expected to receive about $34 more in benefits over the next six months than a similar household that was already at the new income level. Over the first 12, 18, and 24 months after an earned income increase, those differences would be expected to be about $49, $72, and $81, respectively. These differences represent between 3.4 percent and 5.7 percent of the aggregate earned income increases over those periods. Those percentages may not seem large as compared with estimates of the average EMTR faced by these households of about 80 percent. But those estimates of the

EMTR include more tax and transfer programs and were derived using different methodology than we used above, so our estimates are not directly comparable.

In order to better understand how benefit continuations might affect typical estimates of EMTRs for these programs, we also estimated those EMTRs using two different types of analyses: the dynamic analysis described above in the methods section, and a more typical static analysis. Again, we limited our sample to unmarried households with children and earned incomes between 50 percent and 150 percent of the applicable poverty line. For the dynamic analysis, we again obtained estimates for periods of 6, 12, 18, and 24 months after an earned income increase. For the static analysis, we used the same controls and mixed-effects regression model as in the dynamic analysis, but simply regressed the monthly benefits received by the household on the household's earned income in the same month. We summarize all of these estimates in Table 4, which again presents only the single coefficient of interest and the sample size for each regression.

Table 4

Static and Dynamic Estimates of Effective Marginal Tax Rates under Three Transfer Programs after an Earned Income Increase [and 95% Confidence Intervals]

Length of Period After Earned Income Increase	Estimated Effective Marginal Tax Rate for Program				
	MEDICHIP	SNAP	School Nutrition	Three Program Total	Obs./HH
Static analysis[a]	-0.019	-0.043***	-0.005	-0.063***	12,241/939
	[-0.045, 0.006]	[-0.064, -0.022]	[-0.013, 0.003]	[-0.097, -0.028]	
6 months[b]	-0.010**	-0.016***	-0.002**	-0.027***	7,811/723
	[-0.020, 0.000]	[-0.022, -0.010]	[-0.005, -0.000]	[-0.042, -0.012]	
12 months[b]	-0.017	-0.024***	-0.004*	-0.043**	5,812/530
	[-0.041, 0.006]	[-0.039, -0.008]	[-0.007, 0.000]	[-0.082, -0.004]	
18 months[b]	-0.021	-0.026***	-0.004**	-0.049**	4,298/450
	[-0.052, 0.010]	[-0.046, -0.007]	[-0.008, -0.000]	[-0.097, -0.001]	
24 months[b]	-0.025*	-0.022*	-0.004	-0.049*	3,082/343
	[-0.055, 0.005]	[-0.047, -0.003]	[-0.010, 0.001]	[-0.099, 0.002]	

a. Sample includes only households (a) that had no elderly or disabled members; (b) that were headed by a single person; (c) with at least one child younger than age 18; and (d) whose earned income during the current month was between 50 percent and 150 percent of the applicable poverty line. All models are maximum likelihood panel data regressions with random intercepts at the state and household levels; with robust standard errors to adjust for clustering at the state level; and with controls for the applicable poverty line during the current month, for the current SIPP survey reference month, and for certain demographic variables relating to the head of the household in the current month (sex, race, whether Spanish/Hispanic/Latino, whether born in the U.S., and years of education).

b. Samples include only households (a) that had no elderly or disabled members; (b) that did not change in size, composition, or state of residence from the earliest month to the current month; (c) that were headed by a single person; (d) with at least one child younger than age 18; (e) whose earned income increased or remained constant from the earliest month to the immediately subsequent month; and (f) whose earned income during the earliest month was between 50 percent and 150 percent of the applicable poverty line. All models are maximum likelihood panel data regressions with random intercepts at the state and household levels; with robust standard errors to adjust for clustering at the state level; and with controls for the household's earned income during the earliest month, for the household's earned income changes during each month subsequent to the second month up to and including the current month, for the applicable poverty line during the current month, for the current SIPP survey reference month, and for certain demographic variables relating to the head of the household in the current month (sex, race, whether Spanish/Hispanic/Latino, whether born in the U.S., and years of education).

* $p < .10$. ** $p < .05$. *** $p < .01$.

The estimated EMTRs associated with MEDICHIP, SNAP, and School Nutrition programs in the static analysis would be about 1.9 percent, 4.3 percent, and 0.5 percent, respectively. Considering all three programs together, the estimated EMTR would be about 6.3 percent. But in the dynamic analyses considering the first 6, 12, 18, and 24 months after an earned income increase, the total estimated EMTR for all three programs would be about 2.7 percent, 4.3 percent, 4.9 percent, and 4.9 percent, respectively. Thus, in those first 6, 12, 18, and 24 months, the benefit continuations estimated above in Table 3 would reduce the estimated EMTR for all three programs from the static analysis by about 57 percent, 32 percent, 22 percent, and 22 percent, respectively.

An additional point merits some discussion with respect to our static estimates of the EMTRs for these programs in Table 4. In particular, those estimates are lower than most prior static estimates of those EMTRs. As the CBO (2012b) explained, households in this income range that are receiving SNAP benefits would lose up to 24 cents in benefits for each additional dollar of household income. And adults in almost all states would cross the upper income eligibility limit for Medicaid coverage between 50 percent and 150 percent of the applicable poverty line, although children and pregnant women would retain coverage under MEDICHIP until higher percentages of the applicable poverty line in almost all states (Heberlein et al., 2012). Finally, all households would cross the income eligibility limit for free school meals at 130 percent of the applicable poverty line, and would then fall within the income range for reduced-price meals until their income reached 185 percent of the applicable poverty line. So, one might expect the combination of reduced SNAP benefits, the possible loss of adult Medicaid coverage (at a monthly market value ranging from $929 to $8,838 in our data), and the possible transition from free to reduced-price school meals (at a monthly difference in value ranging from $6 to $84 in our data) to contribute to a higher EMTR than our 6.3 percent estimate.

There are likely at least three reasons why our estimates are lower than most prior static estimates of the EMTRs for these programs. First, prior estimates often applied only to households participating in the programs, whereas our estimates apply to all unmarried households with children and earned incomes in the specified income range. As shown in Table 1, less than 60 percent of these households actually participated in each program (54 percent for MEDICHIP, 37 percent for SNAP, 59 percent for school lunch programs, and 43 percent for school breakfast programs). Second, as noted above and discussed further below, households are believed to underreport their MEDICHIP and SNAP benefits in the SIPP by 15 to 20 percent, which might affect our EMTR estimates. Finally, our use of a mixed-effects regression model allowed us to control for household-specific factors (in addition to the demographic control variables) that affect both income and benefits. An analysis that fails to do so might overestimate the relationship between income and benefits. Indeed, when we performed the same analyses using regression models that rely on variation between households (and thus do not control for these omitted household-specific factors), such as pooled ordinary least squares and between-effects models, our estimates were much higher, with total estimated EMTRs for all three programs between 25 percent and 27 percent. In any event, our primary objective here was not to estimate EMTRs; it was to consider how benefit continuations under these programs might affect static estimates of those EMTRs.

Discussion

We next consider the implications of our estimates for these three programs with respect to broader discussions about EMTRs under tax and transfer programs generally. It was not our objective here to do a full dynamic analysis of EMTRs under tax and transfer programs. Therefore, we cannot directly compare EMTRs from a full dynamic analysis to those obtained from prior static analyses; we can only extrapolate from our results.

First, it is important to recognize that our estimate that benefit continuations under these three programs during the first 6 months after an earned income increase may offset about 57 percent of the estimated benefit phaseouts under the programs from a static analysis is, if anything, likely to be conservative. As noted above, households are believed to underreport their receipt of means-tested benefits in the SIPP. In particular, the SIPP has been estimated to capture only about 80 to 85 percent of actual MEDICHIP and SNAP benefits and beneficiaries (Meyer, Mok & Sullivan, 2009; Wheaton, 2007), although it has been estimated to capture more than 100 percent of NSLP beneficiaries (Meyer, Mok & Sullivan, 2009). After households experience an income increase, it seems more likely that they would underreport benefits to a greater extent than to a lesser extent. Therefore, if underreporting of benefits affects our results, it is likely that the actual percentage of estimated benefit phaseouts offset by these benefit continuations during the first six months after an earned income increase would be even larger than 57 percent.

Nevertheless, we will use our estimates above to consider the potential effect of benefit continuations under means-tested transfer programs more generally on EMTRs for low- and moderate-income households. In the CBO's (2012b) analysis for single-parent households in Pennsylvania with one child and incomes between 50 percent and 150 percent of the poverty line, EMTRs associated with just three means-tested transfer programs (SNAP, TANF, and Housing Vouchers) averaged about 50 percent, whereas EMTRs associated with taxes averaged about 30 percent. Thus, even without including other means-tested transfer programs such as MEDICHIP, subsidized child care, other public housing programs, and Head Start, the EMTRs associated with means-tested transfer programs represented about five-eighths of the total estimated EMTRs for these households. Our own estimates for these households in Illinois including all of those transfer programs are similar, with benefit phaseouts under means-tested transfer programs representing about 70 percent of the total estimated EMTRs for these households (Reinbold, 2013). Therefore, if benefit continuations under means-tested transfer programs generally are consistent with our estimates for MEDICHIP, SNAP, and School Nutrition programs, they could offset about 40 percent (57 percent of 70 percent) of the total estimated EMTRs for these households during the first six months after an income increase.

Of course, this result would not undermine the conclusion that low- and moderate-income households with children may face unreasonably high EMTRs. Even if benefit continuations do offset 40 percent of those EMTRs during the first six months after an income increase, these households would still lose about fifty cents of every dollar increase in their incomes to taxes and benefit phaseouts during those first six months, and an even greater percentage in subsequent months. Those losses would still be larger than for any households (married or unmarried, with or without children) with incomes above 200 percent of the applicable poverty line in the CBO's estimates. So, concerns about the effects of these losses on the incentives for low- and moderate-income households with children to earn additional income and on the inequality-reducing effects of means-tested transfer programs would remain, although they would be slightly reduced.

However, our results may help explain why low- and moderate-income households do not react as expected to their high EMTRs. Most research has indicated that, although these households respond to very low EMTRs associated with the phase-in of benefits under programs like the Earned Income Tax Credit (EITC) by working more, they do not seem to respond to high EMTRs associated with the phaseout of those benefits by working less (Eissa & Liebman, 1996; Gruber & Saez, 2002; Keane & Moffitt, 1998; Meyer, 2002) (except for married women, who may have reduced their work effort in response to the EITC phaseout (Eissa & Hoynes, 1998; Ellwood, 2000)). It is possible that these households may not fully understand their high EMTRs (Romich & Weisner, 2000; Meyer, 2002). And even if they do understand those EMTRs, they may be unable to respond to them because of their inability to reduce their work effort by small amounts (Romich, 2006).

Romich (2006) used ethnographic data on 40 low-income households in Wisconsin to examine why low-income households do not respond as expected to high EMTRs. Her research confirmed that these households often did not fully comprehend their marginal incentives. In particular, she concluded that they often understood the general principles behind means-tested transfer programs, but not the specific benefit structures. But she also observed that most household income increases did not result in benefit losses, because they did not move the household to a different level on the benefit schedule or because the income increases were temporary and did not coincide with benefit recertification points. Therefore, consistent with our results, perhaps one of the general principles that these households have learned is that income increases do not always result in benefit losses, at least not immediately. This knowledge would reduce their work disincentives, which might help explain why they do not reduce their work effort as expected.

As ours is the first study that we are aware of that considers the magnitude of these benefit continuations under means-tested transfer programs and their effect on EMTRs, we believe that further research is needed in several areas. First, there is a need for full dynamic analyses of EMTRs, estimating those EMTRs not only across income levels, household types, and states, but also over time. Perhaps the simulation programs used for many of the prior estimates of EMTRs could even be refined to enable dynamic analyses. Second, analyses of the means-tested transfer programs that we considered above could be replicated with other data sources, methods, or assumptions (including with respect to the valuation of MEDICHIP benefits) to further assess the robustness of our results. Third, similar analyses could be done for other means-tested transfer programs, to test the soundness of our extrapolation above from our results for the three programs that we considered to means-tested transfer programs generally. In any case, if we want to better understand how low- and moderate-income households experience means-tested transfer programs, we need to follow and analyze them over time, preferably with even better data than that collected in the SIPP and similar surveys.

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