THREE ESSAYS ON OBESITY, POVERTY, AND THE LABOR MARKET

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THREE ESSAYS ON OBESITY, POVERTY, AND THE LABOR MARKET

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This dissertation broadly examines the economic and health-related consequences of individual behaviors, and their interaction with government programs. It is divided into three distinct chapters.

The first chapter examines how changes in family income contribute to increasing obesity among low-income families. In the general adult female population, the prevalence of obesity decreases substantially as family income increases. However, this relationship is not necessarily causal, as numerous other factors could be driving this negative correlation. I make use of the expansion of the New York State Earned Income Tax Credit (EITC) program over the course of the 1990s as a source of exogenous variation in family income in order to estimate the causal effect of family income on obesity. I show that increasing family income has a positive effect on weight and obesity prevalence among the sample population. This effect is concentrated among those who are already obese.

The second chapter simulates the effect on New York State residents of an expansion of the EITC on employment, hours worked, income, and poverty, and compares these results to a simulation which excludes labor supply effects. Relative to estimates excluding labor supply effects, the preferred behavioral results show that an expansion of the New York State EITC increases employment by an additional 14,244 persons, labor earnings by an additional $95.8 million, and family income by an additional $84.5 million; decreases poverty by an additional 56,576 persons; and increases costs to the State by $29.7 million.

The third chapter is a co-authored work with Richard Burkhauser and John Cawley. It returns to the topic of obesity, and investigates which measures of fatness most accurately predict application for Social Security Disability (DI) benefits. Although the social science literature has wholly embraced the use of body mass index (BMI) as a measure of fatness, many medical researchers argue that BMI is a poor measure of a person's true fatness. Our results indicate that despite the limitations of BMI, it is consistently a significant predictor of future application for DI, although more accurate measures of fatness occasionally perform better as predictors of application.

BIOGRAPHICAL SKETCH

Maximilian Schmeiser was born in 1982 in Regina, Canada. He attended the University of Regina in Regina, Canada, from 2000 to 2003 and received a B.A. in Economics in May of 2003. He then undertook graduate studies at McMaster University in Hamilton, Canada, from 2003 to 2004, and received his M.A. in Economics in November of 2004. He continued his graduate education at Cornell University beginning in August of 2004, received his M.S. in Policy Analysis and Management in May of 2007, and his Ph.D. in August of 2008. He has accepted a position as an Assistant Professor at the University of Wisconsin-Madison.

Dedicated to my parents, Daniel and Maryanne Schmeiser. Without their support none of this would have been possible.

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Abstract

The rising rate of obesity has reached epidemic proportions and is now one of the most serious public health challenges facing the U.S. (U.S. DHHS, 2001). But the underlying causes for this increase are unclear. This paper adds to the literature on this topic by exploring the importance of family income for obesity using data from the National Longitudinal Survey of Youth 1979 cohort. It does so by using exogenous variation in family income in a sample of low-income women and men obtained from the correlation of their family income with differences in the level of their state's Earned Income Tax Credit (EITC) supplement at a point in time and variations in the value of federal and state EITC benefits over time. Income significantly raises the BMI of EITC–eligible women, and has no appreciable effect on the BMI of EITC-eligible men. An additional $1,000 increases women's (men's) BMI by 0.24 (0.07) units or 1.4 (0.5) pounds. These results imply that family income increases from 1990 to 2002 explain 15 percent of women's BMI increases and 3 percent of men's BMI increases in the sample.

JEL classifications: I12; I18; I38

Keywords: Obesity; Body Mass Index; EITC

1.1. Introduction

The weight of Americans has increased significantly over the past 30 years with the average weight of men and women age 20 to 74 increasing by 9 percent and 12 percent, respectively (Ogden et al., 2004). Moreover, these trends understate increases in the level of obesity, which has more than doubled in the past 30 years, rising from 15 percent to over 30 percent for persons age 20 to 74 (Flegal et al., 2002; Hedley et al., 2004). [1] Excessive fatness, or obesity, is now recognized as one of the most serious public health challenges facing the U.S. (U.S. DHHS, 2001) and other industrialized countries (International Obesity Task Force, 2005). Previous research into the determinants of obesity and its increasing prevalence has been pointed to, among other things, falling food prices, technological innovation in food processing, increasing female labor force participation, and reduced smoking (Anderson et al., 2003; Chou et al., 2004; Cutler et al., 2003; Lakdawalla and Philipson, 2002). However, this research has largely ignored the role of rising income. Further, the work that has examined the role of income has produced correlational, rather than causal, estimates of its role in the increase in weight and obesity prevalence.

Previous correlational estimates of the impact of income[2] on obesity within the Unites States are limited by their failure to account for unobserved factors which could be simultaneously affecting an individual's income and weight or the potential for BMI to affect income (See Cawley, 2004). In contrast, this paper estimates the causal impact of family income on body mass index (BMI) using an instrumental variables (IV) estimation strategy. It does so within a panel data set of women and men, in which exogenous variation in their family income is obtained using the correlation of their family income with differences in the level of their state Earned Income Tax Credit (EITC) supplement at a point in time and variations in the value of federal and state EITC benefits over time.

[1] Obesity is defined as a body mass index (BMI) value greater than or equal to 30 where BMI is calculated as the ratio of weight in kilograms to height in meters squared or weight in pounds to height in inches squared multiplied by 703 (NIH, 1998).

[2] Previous studies attempting to explain the rise in weight and obesity have used various measures of income including family income (Anderson et al., 2003), household income (Chou et al, 2004; Lakdawalla and Philipson, 2002; Quintana-Domeque, 2005), Social Security income (Cawley et al., 2007), and wage rate (Lakdawalla and Philipson, 2002).

The rationale for focusing on the relationship between family income and BMI, as opposed to family income and the consumption and expenditure of calories, is that the quality of data on caloric intake and expenditure is inaccurate at best, non-existent at worst. Ideally, data would be available detailing the exact number of calories an individual consumes, broken down by the sources of those calories (fat, protein, sugars, etc.). This would allow for the estimation of an income-consumption path of calories, that is we could investigate how the consumption and expenditure of calories varied with family income. Unfortunately, those data do not exist, thus the relationship between family income and BMI is estimated, where BMI is used as a stock measure of past consumption and expenditure of calories.

This paper proceeds in the following manner. The second section of this paper discusses the consequences and policy implications of rising obesity and provides background on the EITC program. The third section reviews the literature on income and weight. The fourth section details the data used in the analysis. The fifth section outlines the identification strategy and empirical methods, while the sixth section provides the empirical results. The paper concludes with a discussion of the results.

1.2. Background

1.2.1. Consequences of Obesity

Understanding the causal association between income and weight would contribute to improved estimates of the relative causes of the increasing prevalence of obesity. Knowledge of the factors contributing to rising obesity would allow for the undertaking of more effective measures to slow down, or ideally reverse, the current sharp upward trend in obesity prevalence. The concerns about the increasing prevalence of obesity are founded in the association between obesity and adverse health outcomes and increased health expenditures. Obesity has been linked to an increased risk of numerous comorbidities, including high blood pressure, high blood cholesterol, type II diabetes mellitus, coronary heart disease, osteoarthritis, asthma, and gallbladder disease (Must et al., 1999; Mokdad et al., 2003). Moreover, obesity has been found to significantly lower life expectancy, particularly among young adults (Fontaine et al., 2003). With the rise in obesity, poor diet and physical inactivity have now become the number two preventable cause of death in the United States, behind only tobacco in the number of lives claimed each year (Mokdad et al., 2004; 2005).

The numerous obesity-related illnesses invariably lead obese persons to have higher medical expenditures than the non-obese. Finkelstein et al. (2003) estimate that, on average, annual medical expenditures for obese persons are 37 percent higher than for non-obese persons. They also estimate that obesity-related illnesses are responsible for 9.1% of U.S. health expenditures, or $92.6 billion (2002 dollars) and that half of these expenditures are covered by Medicare and Medicaid. Thus obesity and obesity-related illnesses also have implications for taxpayers and the federal budget. Aside from increasing Medicare and Medicaid expenditures, the high prevalence of obesity may have important implications for the solvency of the social security system, as obesity has been linked to the decision to take early Social Security retirement benefits (Burkhauser and Cawley, 2006).

1.2.2. Background on the EITC Program

Originally enacted in 1975 to offset the payroll taxes of workers with low earnings, the federal EITC was expanded in scope and size in 1986, 1990 and most recently in 1993. It is now the Nation's largest anti-poverty program for non-elderly individuals with expenditures of nearly $41.5 billion and over 22 million recipients in tax year 2005 (Center on Budget and Policy Priorities, 2007). Available only to those with labor earnings, the EITC acts as a wage subsidy, providing an incentive for those not working to enter the labor force. For those already employed, the effect of the EITC on hours worked is more ambiguous—it is dependent on the relative size of the compensated and uncompensated labor supply elasticities. Figure 1.1 displays the three distinct earnings ranges over which the EITC operates for tax year 2007**.** Total benefits rise during the phase-in range of the credit (Points A to B), with different credit rates and maximum benefit values for single childless individuals, families with one eligible child, and families with two or more eligible children. At some labor earnings level, called the plateau range, no new benefits are earned as labor earnings increase, but the credit is not reduced (Points B to C). At a still higher level of labor earnings, the phase-out range begins and total benefits fall with additional earnings (Points C to D). This continues until EITC benefits decline to zero: the breakeven point. As shown in Table 1.1, in 2007 the federal EITC provided childless individuals with a maximum benefit of $428; families with one child a maximum benefit of $2,853; and families with two or more children a maximum benefit of $4,716. A detailed discussion of the structure of the federal EITC program and its theoretical labor supply effects is provided in the Appendix.

In addition to the federal EITC, as of January 2006 19 states and the District of Columbia operate their own supplemental EITC programs. The history and generosity of each state's EITC is presented in Table 1.2. The value of a taxpayer's state EITC is generally set as a fraction of their federal EITC.[3] The state credits vary significantly in terms of their generosity relative to the federal EITC, and not all are refundable.[4]

[3] Minnesota's EITC is not linked to the federal EITC program.

[4] As of January 2006, State EITC programs exist in: Colorado; Delaware; D.C.; Illinois; Indiana; Iowa; Kansas; Maine; Maryland; Massachusetts; Minnesota; New England; New Jersey; New York; Oklahoma; Oregon; Rhode Island; Vermont; Virginia; and Wisconsin.

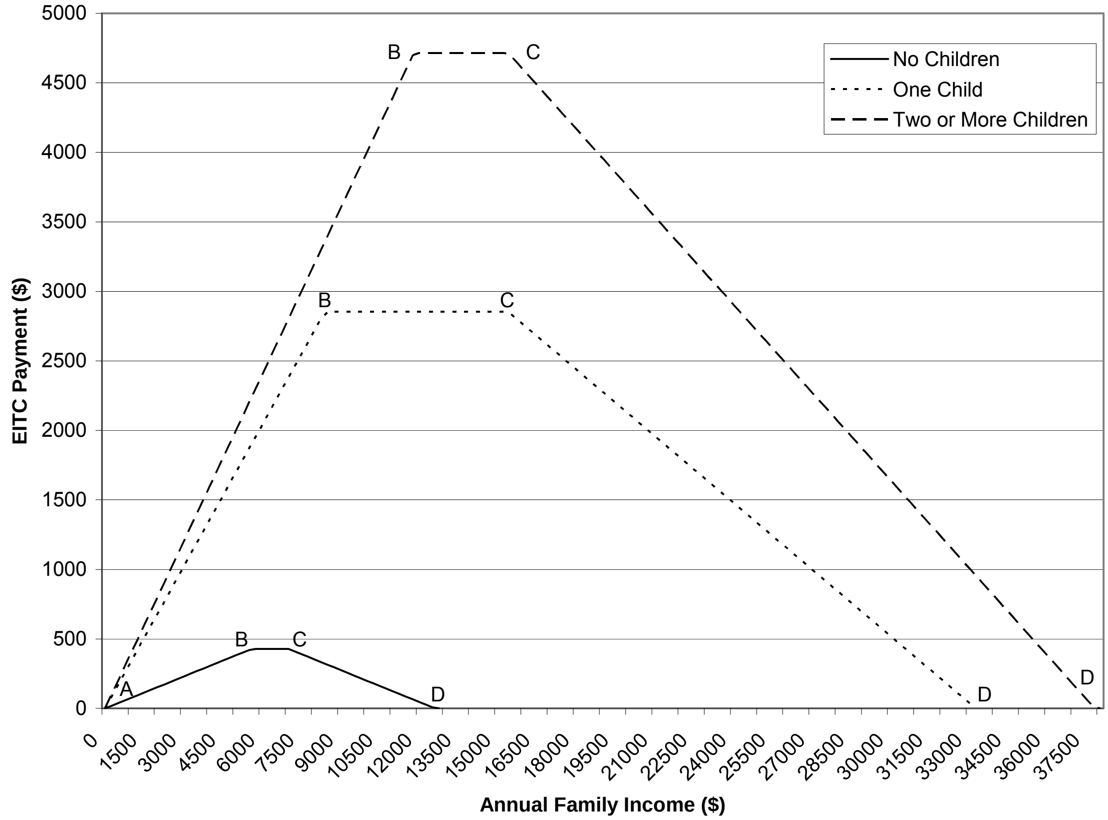

Figure 1.1. Credit Regions of the Federal EITC Program for Tax Year 2007

Table 1.1. 2007 Earned Income Tax Credit Parameters

Type of Return	Maximum Eligible Earnings	Maximum Credit	Begin Phase-out	Breakeven Point	Credit Rate	Phase-out Rate
Childless	$5,590	$428	$7,000	$12,590	7.65%	7.65%
1 Child	$8,390	$2,853	$15,390	$33,241	34.00%	15.98%
2 or More Children	$11,790	$4,716	$15,390	$37,783	40.00%	21.06%

Note: Married Filing Jointly have Phase-out and Breakeven point $2,000 above listed values.

Source: Urban Institute and Brookings Institute Tax Policy Center http://www.taxpolicycenter.org/TaxFacts/TFDB/TFTemplate.cfm?Docid=368

Table 1.2. State EITC supplements 1984-2002 (Percent of Federal EITC Credit)

State:	CO	DE	DC	IL	IA	IN	KS	ME	MD	MA	MN	MN	NE	NJ	NY	OK	OR	RI	VA	VT	WI	WI	WI
# of children:									1+			1+			1+						1	2	3+
Tax Year:																							
1984																					30	30	30
1985																					30	30	30
1986																		22.21					
1987																		23.46					
1988																		22.96		23			
1989																		22.96		25	5	25	75
1990					5													22.96		28	5	25	75
1991					6.5						10	10						27.5		28	5	25	75
1992					6.5						10	10						27.5		28	5	25	75
1993					6.5						15	15						27.5		28	5	25	75
1994					6.5						15	15			7.5			27.5		25	4.4	20.8	62.5
1995					6.5						15	15			10			27.5		25	4	16	50
1996					6.5						15	15			20			27.5		25	4	14	43
1997					6.5					10	15	15			20		5	27.5		25	4	14	43
1998					6.5		10		10	10	15	25			20		5	27		25	4	14	43
1999	8.5				6.5		10		10	10	25	25			20		5	26.5		25	4	14	43
2000	10		10	5	6.5		10	5	15	10	25	25		10	22.5		5	26		32	4	14	43
2001	10		25	5	6.5		10	5	16	15	33	33		15	25		5	25.5		32	4	14	43
2002	0		25	5	6.5		15	5	16	15	33	33		17.5	27.5	5	5	25		32	4	14	43

Source: Leigh (2004), P.5

1.3. Literature Review

Cross-nationally, a positive correlation between income and weight exists, with the prevalence of obesity being far greater in developed countries than less developed countries, and obesity rates increasing as per capita incomes increase (WHO, 2003; Seidell and Rissanen, 1998; Swinburn et al., 2004). Within less-developed nations, those of higher socioeconomic status are more likely to be obese (Sobal and Stunkard, 1989). However, for women in the U.S., the opposite is true: the prevalence of obesity is lower among those of higher socioeconomic status. For men in the U.S., obesity prevalence is relatively constant across family income, while the prevalence of overweight increases with household income. Tables 1.3 and 1.4 report clinical weight classification by household income for American men and women based on data from the 2005 Centers for Disease Control and Prevention Behavioral Risk Factor Surveillance System (BRFSS).[5] Table 1.3 shows that obesity rates for men are approximately 27 percent across household income categories. In Table 1.4, which presents clinical weight classification for women, a strong negative correlation between household income and obesity is apparent, with the prevalence of obesity for those women with household incomes less than $15,000 per year (36 percent) being more than twice that of women with household incomes of more than $75,000 per year (16 percent). The dichotomy between the cross-national and intra-U.S. correlation of income and obesity prevalence suggests that once basic nutritional needs have been met—as they are for nearly all persons in the U.S.—a different set of factors drive the relation between income and obesity.

[5] BRFSS data are used as opposed to National Longitudinal Survey of Youth 1979 Cohort (NLSY79) data, as, for a given year, the NLSY79 only captures persons within a 9 year age range. For example, in the 2002 wave there are persons between the ages of 37 and 45. However, the cross-tabulation of income and clinical weight classification is qualitatively similar using the NLSY79 data.

Table 1.3. Weight Classification by Household Income for Men Age 18-64

Annual Household Income	Weight Classification			
	Neither Overweight nor Obese	Overweight	Obese	Overweight and Obese
Less than $10k	41.19%	32.28%	26.53%	58.81%
$10k-15k	36.03%	36.31%	27.66%	63.97%
$15k-20k	36.55%	35.81%	27.65%	63.45%
$20k-25k	35.38%	37.11%	27.52%	64.62%
$25k-35k	32.51%	39.97%	27.52%	67.49%
$35k-50k	30.07%	42.44%	27.50%	69.93%
$50k-75k	25.25%	46.76%	27.99%	74.75%
>$75k	26.16%	49.22%	24.62%	73.84%
Overall	29.20%	44.19%	26.61%	70.80%

Source: Centers for Disease Control and Prevention Behavioral Risk Factor Surveillance System 2005

Table 1.4. Weight Classification by Household Income for Women Age 18-64

Annual Household Income	Weight Classification			
	Neither Overweight nor Obese	Overweight	Obese	Overweight and Obese
Less than $10k	38.30%	26.09%	35.61%	61.70%
$10k-15k	38.50%	25.24%	36.27%	61.50%
$15k-20k	37.33%	27.11%	35.56%	62.67%
$20k-25k	38.21%	28.89%	32.90%	61.79%
$25k-35k	40.63%	29.53%	29.84%	59.37%
$35k-50k	42.75%	30.00%	27.24%	57.25%
$50k-75k	46.80%	29.11%	24.09%	53.20%
>$75k	57.96%	26.50%	15.54%	42.04%
Overall	46.70%	28.12%	25.18%	53.30%

Source: Centers for Disease Control and Prevention Behavioral Risk Factor Surveillance System 2005

The cross-national income-based differences in obesity prevalence have been attributed to the fact that higher incomes may lead to (or result from) more sedentary lifestyles (Popkin, 2001; Drewnowski, 2000). Similarly, Lakdawalla and Phillipson (2002) suggest that labor and non-labor income may differentially affect weight to the extent that the level of physical activity expended in an hour of labor varies from the level of physical activity expended during an hour of leisure time. As technological innovation decreases the level of physical activity expended on work, income earned through the labor market should increase weight more than income earned through the asset market. They argue that there is greater variance in the level of technology between countries than there is within countries, leading the effect of non-labor earnings to dominate the effect of labor earnings within countries, while the opposite occurs between countries, leading to the observed dichotomy in cross-national and intra-national obesity-income correlations.

This paper focuses on the within-country relationship between family income and weight, generating causal estimates of how family income impacts weight in the U.S. Correlational estimates of the relationship between income and weight may not accurately capture the causal relationship, as there are numerous unobserved factors which could be simultaneously affecting income and weight, such as genetics, environment, and health status. In addition, income may be causally affected by weight; Cawley (2004) finds evidence that for obese white women, weight lowers wages. Failure to account for endogeneity or reverse causality between income and weight would render OLS estimates biased and inconsistent. In order to overcome these concerns, several studies have taken an IV approach to estimating the causal impact of income on weight

Using the European Community Household Panel (ECHP), Quintana-Domeque (2005) makes use of the exogenous variation in family income resulting from receipt of inheritance, gifts, or lottery winnings of 2000 Euros or more to instrument for income. Unfortunately, the instrument is quite weak with an F-statistic well below 10 in the first stage. Results show that, the 9 nations included in the survey, statistically significant estimates of the impact of income on weight are only found for Denmark and Italy, in the case of women, and Finland in the case of men. In all three of these cases the estimated BMI-Income elasticity is found to be negative.

Cawley et al. (2007) exploit the Social Security "notch", which unintentionally provided double indexation against inflation for certain birth cohorts—leading those in the notch to have higher Social Security incomes than those not affected by the notch—as an instrument for Social Security income. Though their instrument appears to be quite powerful, they are unable to identify any statistically significant relationship between additional Social Security income and weight for either men or women. However, given the instrument used, the results represent a local average treatment effect for a relatively small segment of the population: the low-income elderly.

This study contributes to the existing literature by generating causal estimates of the impact of family income on BMI and the probability of being overweight and/or obese for women and men eligible for the Earned Income Tax Credit (EITC). This study significantly expands the population for which causal estimates of the effect of family income on BMI have been generated, and, though changes in the federal EITC program have previously been used to estimate the impact of income on child development (Dahl and Lochner, 2005) it further highlights the validity of this instrument and introduces an additional source of exogenous variations in income from the state EITC programs.

1.4. Data

This paper uses data from the restricted-access National Longitudinal Survey of Youth 1979 cohort (NLSY79). The NLSY79 is a nationally representative sample of individuals who were between the ages of 14 and 21 on December 31, 1978. The first wave of the NLSY79 contained information on 12,686 individuals, including an oversample of poor and minority families. NLSY79 interviews were conducted annually from 1979 to 1994, and biennially since 1994. This paper makes use of the 1990 through 2002 waves of the NLSY79 (Tax Years 1989 through 2001), as the major changes in the Earned Income Tax Credit program occurred beginning in tax year 1991.

The outcome of interest, BMI, and the clinical weight classifications derived from BMI, are constructed using self-reported weight and height data. A respondent's weight is asked in each wave of the NLSY79, while height is asked in only the 1981, 1982, and 1985 waves of the NLSY79. In order to construct BMI for each wave from 1990 through 2002 I make use of weight from the relevant wave the NLSY79 and the 1985 height of respondents. As all respondents are at least 20 years of age in 1985 their height in 1985 should represent their final adult height and remain constant through the end of the sample period examined here. Given that self-reported weight and height are known to contain measurement error, the self-reported values from the NLSY79 are adjusted by race and gender using the method provided in Cawley and Burkhauser (2006). Moreover, as pregnancy distorts a woman's weight, 351 pregnant women are excluded from the sample.

Table 1.5 presents mean BMI and mean adjusted BMI for the EITC eligible sample of women and men employed in the regression in the first and last year of the sample period (1990 and 2002), as well as the prevalence of overweight/obese and obesity calculated using unadjusted and adjusted BMI. Adjusting weight and height for measurement error increases the mean BMI of women in 1990 from 26.48 to 27.24, and from 29.18 to 29.97 in 2002. For men, the adjustment resulted in 1990 mean BMI increasing from 26.32 to 27.84 and 2002 mean BMI increasing from 28.18 to 29.74. Thought the change in mean BMI due to the adjustment in weight and height appears minor, it results in the prevalence of obesity for women increasing by nearly

22 percent in 1990 from 23.11 percent unadjusted to 28.14 percent when adjusted, and by 8.5 percent in 2002, going from 38.33 percent unadjusted to 41.60 percent when adjusted. For men the adjustment resulted in even more substantial change, with the prevalence of obesity increasing by 61 percent in 1990 from 17.85 percent unadjusted to 28.82 percent when adjusted, and by 37 percent in 2002, going from 29.23 percent unadjusted to 40.00 percent when adjusted. The correlation between BMI and adjusted BMI and obesity prevalence and adjusted obesity prevalence are both quite high, with coefficients of 0.99 and 0.90, respectively.

The data from the NLSY were merged with the characteristics of the federal EITC program from the House Ways and Means Committee Green Book 2004, and the characteristics of state EITC programs from Leigh (2004). To account for the effect of smoking on weight data on the average price of a pack of cigarettes was obtained from various years of Orzechowski and Walker's *Tax Burden on Tobacco*. These prices were adjusted to 2005 dollars using the Bureau of Labor Statistics annual Consumer Price Index (CPI).

Since food prices in general, and the relative price of fast-food to home cooked meals, are likely to affect weight, two corresponding food price indices are constructed. Data on fast-food meal prices and food for home consumption came from the prices in the ACCRA *Cost of Living Index* published by the Council for Community and Economic Research. The state-specific real fast-food meal price index included in the model was constructed from the price of a McDonald's Quarter-Pounder with Cheese, an 11"-12" thin crust cheese pizza from Pizza Hut or Pizza Inn, and a thigh and drumstick from Kentucky Fried Chicken or Church's. As prices are presented on a quarterly basis at the city level, the fast-food prices were averaged across cities within a state to form quarterly state prices. The state prices were then averaged across the four-quarters in a given year to form annual prices. The real fast-food price index was constructed by taking a budget share weighted average of the three fast-food prices and dividing by the ACCRA Cost of Living Index.

The procedure for calculating the real food for home consumption price index was identical to that used to calculate the fast-food price index. The real food for home consumption index used the prices of 22 food items available in the ACCRA Cost of Living Index: a pound of T-Bone Steak; a pound of ground beef; a pound of Jimmy Dean or Owens brand pork sausages; a pound of frying chicken; a 6 oz can of Starkist or Chicken of the Sea chunk light tuna; half a gallon of whole milk; one dozen Grade A large eggs; one pound of Blue Bonnet or Parkay brand margarine; 8 oz canister of Kraft brand grated parmesan cheese; 10 lbs white or red potatoes; a pound of bananas; a head of iceberg lettuce; a 24 oz loaf of white bread; an 11.5 oz can of Maxwell House, Hills Brothers, or Folgers coffee; a 4 pound sack of sugar; an 18 oz box of Kellogg's Corn Flakes or Post's Toasties; a 15-17 oz can of Del Monte or Green Giant brand sweet peas; a 14.5 oz can of Hunt's or Del Monte tomatoes; a 29 oz can of Peaches; a 12 oz can of Minute Maid frozen orange juice; a 16 oz bag of frozen whole kernel corn; and a 2 liter bottle of Coca Cola. These 22 items represent the universe of grocery food prices available in the ACCRA data set.

The NLSY sample is divided into those who are eligible for the EITC and those who are not by imputing federal EITC eligibility using the National Bureau of Economic Research (NBER) TAXSIM program. The TAXSIM program is an online tax simulation for calculating liabilities under U.S. Federal and State income tax laws from individual data for tax years 1960 through 2013. The TAXSIM program determined EITC eligibility for the NLSY79 sample on the basis of: the labor income of both the respondent and their spouse; social security income; unemployment insurance income; the respondent's marital status; and the number of children under 18 in the family.

Table 1.5. Unadjusted and Adjusted BMI and Clinical Weight Classification for NLSY79 Sample

	1990		2002		Entire Sample Period: 1990-2002	
	Unadjusted BMI	Adjusted BMI	Unadjusted BMI	Adjusted BMI	Unadjusted BMI	Adjusted BMI
Mean BMI Women	26.48	27.24	29.18	29.97	27.59	28.34
Percent of Women Overweight/Obese (BMI ≥25)	51.13	56.32	67.27	69.87	57.68	62.34
Percent of Women Obese (BMI ≥30)	22.91	27.76	38.31	41.55	30.27	34.54
Mean BMI Men	26.32	27.84	28.18	29.74	27.21	28.73
Percent of Men Overweight/Obese (BMI ≥25)	55.91	67.10	73.65	80.58	63.00	73.93
Percent of Men Obese (BMI ≥30)	17.85	28.82	29.23	40.00	23.81	34.60

Source: Author's calculations using 2005 BRFSS

Restricting the sample to those eligible for the EITC and those women who are not pregnant, combined with missing values for height, weight, income, etc. all waves of the NLSY79 from 1990 to 2002 together yield a final value of 7,310 observations for women, and 4,372 observations for men. As the NLSY79 is a longitudinal data set, multiple observations are available on most persons in the sample. However, as the identification method employed here depends on EITC eligibility, and the sample persons move in and out of EITC eligibility, the data are used as a repeated cross-section.

1.5. Empirical Methods

1.5.1. Identification Strategy

Over the course of the 1990s, the federal government significantly expanded the EITC program, with the maximum credit available to taxpayers with two or more qualifying children increasing in real terms (2005 dollars) from $1,425 in 1990 to $4,410 in 2000. From tax year 1985 through tax year 1990 a single phase-in rate of 14.0 percent was applied to all taxpayers with qualifying children; however, in tax year 1991 different phase-in rates were applied to taxpayers with one qualifying child and taxpayers with two or more qualifying children. These respective phase-in rates were subsequently increased at different rates. Moreover, in tax year 1994 a small maximum credit of $306 ($403 2005 dollars) was extended to taxpayers with no qualifying children and different phase-in, plateau, and phase-out regions were established for taxpayers for no qualifying children, one qualifying child, and two or more qualifying children.

With regards to state EITC programs, in 1989, the first year of analysis, only 3 states (Rhode Island, Vermont, and Wisconsin) had state EITC program in place. By 2002, the last year of analysis, 15 states and the District of Columbia had EITC programs in place. Moreover, between 1989 and 2002 many states adjusted the generosity of their credits relative to the federal credit both upwards and downwards.

The strategy used to identify the causal effect of family income on BMI involves instrumenting for family income using the maximum combined value of federal and state EITC benefits a family is eligible for based on their number of children. This is a state level value, which only varies for residents by the number of children in their family. Taking the example of an EITC eligible person with two children in New York State observed in the 2002 wave of the NLSY79, their maximum federal EITC benefit for tax year 2001 would be $4,420 ($ 2005) and their maximum state EITC benefit would be $1,326 ($ 2005) for a combined current maximum benefit of $5,746.

The maximum value of combined EITC benefits generates exogenous variation in family income using differences in the level of a state EITC supplement at a point in time and variations in the value of federal and state EITC benefits over time. In order for the maximum value of EITC benefits for which a family is eligible to be a valid instrument, it must be uncorrelated with the error in the second stage (the unobserved determinants of BMI), but correlated with family income. There is no reason to suspect that the large non-linear changes in the federal EITC program that Congress enacted over the last 20 years—shown in Table 1.6—should be related to changes in an individual's weight. Nor should the level and variation in state EITC programs be related to changes in an individual's weight. Moreover, a large body of literature has established a significant relationship between expansions of the EITC and changes in labor supply and thus income.[6]

[6] See Hotz and Scholz (2003) for a review of the literature on the effect of the EITC on employment and hours worked.

Table 1.6. Federal Earned Income Tax Credit Maximum Benefit Amount Tax Year 1989-2001

Tax Year	Maximum Benefit (Unadjusted $)	Maximum Benefit (2005 $)
1989		
No children	0	0
One child	910	1,433
Two children	910	1,433
1990		
No children	0	0
One child	953	1,424
Two children	953	1,424
1991		
No children	0	0
One child	1,192	1,709
Two children	1,235	1,771
1992		
No children	0	0
One child	1,324	1,843
Two children	1,384	1,927
1993		
No children	0	0
One child	1,434	1,938
Two children	1,511	2,042
1994		
No children	306	403
One child	2,038	2,686
Two children	2,528	3,331
1995		
No children	314	402
One child	2,094	2,683
Two children	3,110	3,985
1996		
No children	323	402
One child	2,152	2,679
Two children	3,556	4,426
1997		
No children	332	404
One child	2,210	2,689
Two children	3,656	4,449
1998		
No children	341	409
One child	2,271	2,721
Two children	3,756	4,500
1999		
No children	347	407
One child	2,312	2,710
Two children	3,816	4,473
2000		
No children	353	400
One child	2,353	2,669
Two children	3,888	4,410
2001		
No children	364	401
One child	2,428	2,678
Two children	4,008	4,420

In order to account for possible lags in the time between when either the federal or state EITC program is expanded and when people learn of the change and respond to the new set of incentives this expansion creates a one year lag of the maximum combined value of the federal and state EITC for which a family is eligible is included as an additional instrument.

As a test of the assumption that the instrument used here—the maximum value of the combined federal and state EITC benefit—is only relevant to the EITC-eligible population, IV models were estimated separately for those men and women in the NLSY79 who the TAXSIM program determined are eligible for the EITC, and for those determined ineligible for the EITC. An instrument is considered valid if, in the first stage of the IV regression, the F-statistic testing the hypothesis that the coefficients on the instruments are jointly zero exceeds 10 (Stock et al., 2002). In all models estimated on non-EITC eligible men or women the first stage F-statistic is below 10. For example, the first stage F-statistic on the maximum value of the combined federal and state EITC benefit was 0.42 for all non-EITC eligible women with family income less than $40,000 ($ 2005).

Ideally an instrument for family income would be available for the entire population, allowing for estimates of the causal effect of family income on BMI generally. Instead, by using the maximum value of EITC benefits for which a family is eligible as an instrument the population examined here is restricted to those eligible for the EITC program. However, with over 22 million EITC claims filed for tax year 2005, the EITC eligible population comprises tens of millions of low-income persons—a highly policy relevant group. With 132.8 million individual tax returns filed for tax year 2005 EITC claimants comprise 16.6 percent of all individual tax returns (IRS, 2007). The instrument also has considerable power for this population, with first stage F-statistics well above 10.

1.5.2. Estimation

Breaking the negative correlation between income and BMI for women is exceedingly easy. Table 1.7 presents OLS estimates of the effect of family income on BMI as several covariates are added to the regression. With just family income, or even income and age and age squared in the regression the coefficient on income is negative. However, with the addition of race the coefficient on income becomes positive, and the addition of education further increases the positive coefficient.

Table 1.7. Progressive Estimates of Adjusted Body Mass Index on Family Income for Sample Women

	(1)	(2)	(3)	(4)
Dependent Variable: Adjusted BMI	OLS	OLS	OLS	OLS
Family Income ($1,000s)	-0.0056	-0.0119	0.007	0.0164
	(-0.46)	(-0.94)	(0.56)	(1.36)
Age and Age Squared		X	X	X
Race Dummies			X	X
Education Dummies				X
Observations	7310	7310	7310	7310
R-Squared	0.00	0.01	0.04	0.05

Notes:
(1) Robust t statistics in parentheses. Standard errors clustered by state.
(2) * significant at 10%; ** significant at 5%; *** significant at 1%

The full model used here to estimate the effect of family income on BMI takes the form:

$$BMI_{ist} = \alpha + \beta_1 I_{it} + \beta_2 X_{it} + \beta_3 P_{st} + \varepsilon_{ist} \tag{1}$$

where *i* indexes individuals, s indexes states and t indexes time. The dependent variable BMI_{ist} is the adjusted Body Mass Index of respondent *i* at time *t*, I_{it} is the respondent's total family earnings for the previous calendar year in thousands of dollars, X_{it} is a vector of individual level control variables, P_{st} is a vector of state level control variables and ε_{ist} is the error term.

The vector of individual level controls, X_{it}, includes the variables: age, age squared, hours worked in the previous calendar year, a dummy variable for foreign born status, dummy variables for race/ethnicity (Black, Hispanic, White/Other*[7]), a dummy variable for marital status (single*, married, divorced, widowed), the number of own children ever born, the number of adults in the household, a set of dichotomous variables for the highest level of education achieved (less than high school*, high school, some college, a college degree), and residence in an MSA. The NLSY includes a respondent's score on the Armed Forces Qualifying Test (AFQT), which is derived from the Armed Services Vocational Aptitude Battery (ASVAB), which was administered to NLSY respondents in 1980. The AFQT percentile score is also included as a regressor in order to account for the affect of intelligence, independent of education, on BMI. A set of controls are included for whether or not a respondent participated in AFDC/TANF in the past calendar, or the Food Stamps program, as these may, independent of income, impact BMI. Finally, in order to account for the possibility that health status may be a joint determinant of BMI and income, a self-reported measure of whether or not the respondent was prevented from working by a health condition is included as a regressor.

The vector of state level control variables, P_{st}, includes the average price of a pack of cigarettes, the fast-food price index, and the food for home consumption price index. State fixed-effects are subsequently added to the model to account for the possibility of other unobserved state-level time-invariant determinants of BMI not captured by food prices or cigarette prices. The number of hours worked in the previous calendar could potentially affect BMI; however, it is also potentially endogenous to BMI for the same reasons income is endogenous. Thus, the models are

[7] The asterisk denotes the omitted category for the dummy variables.

run with number of hours worked excluded and then included in order to asses the effect on BMI.

As discussed above, Lakdawalla and Philipson (2002) argue that labor income and non-labor income may have different effects on weight if labor income is obtained through sedentary work which results in a decrease in physical activity relative to leisure time. Cognizant of the potential for labor and non-labor income to differentially affect weight the model was first estimated using labor income and non-labor income separately—and no statistically significant difference was found between the coefficient estimates for labor income and non-labor income for EITC eligible women and men. Therefore, family income is used as the measure of income in all models presented here.

In order to account for the aforementioned endogeneity and reverse causality problems which could bias correlational estimates of the relationship between income and BMI, the method of instrumental variables is employed. The first stage of the IV regression takes the form:

$$I_{ist} = \delta + \gamma EITC_{ist} + \lambda EITC_{ist-1} + \phi X_{it} + \varphi P_{st} + \upsilon_{ist} \qquad (2)$$

Where the dependent variable I_{it} is an individual's total family income for the previous calendar year, the instruments are $EITC_{ist}$, the maximum value of the combined federal and state Earned Income Tax Credit for which an individual was eligible for in the previous tax year based on their number of children, and $EITC_{ist-1}$ a one year lag of the maximum value of the combined federal and state EITC for which an individual was eligible, X_{it} is the vector of demographic characteristics used in Model (1), and P_{st} is the vector of state level characteristics used in Model (1). The maximum value of the EITC for the previous calendar year is used as opposed to the current year's value, as income reported in the NLSY is for the previous calendar year. The parameters of the federal EITC for tax years 1989 through 2001 are included in Table 1.6.

The second stage of the IV model is identical to Model (1) except that wages and earnings I is now replaced by its fitted value $\hat{I}$ from the first-stage regression yielding:

$$BMI_{ist} = \alpha + \beta_1 \hat{I}_{ist} + \beta_2 X_{it} + \beta_3 P_{st} + \varepsilon_{ist} \tag{3}$$

The Model is first estimated by Ordinary Least Squares (OLS) for the sample of EITC eligible men and women, in order to obtain an uninstumented estimate of the relationship between income and BMI, and then IV estimates are obtained. The robustness of the coefficient on family income is tested by excluding then including the number of hours worked in the previous calendar year in order to account for the potential impact of work on weight. Moreover, separate estimations are conducted for those who are working and those who are not working. In all cases work does not appear to significantly alter the effect of family income on BMI.

As pointed out by Cawley et al. (2005) and Kan and Tsai (2004), changes in income may differentially affect individuals at different points in the BMI distribution, and thus least squares-based methods may provide limited information on the effect of income on BMI as these methods could potentially mask large affects at either end of the BMI distribution. In order to explore the relationship between income and BMI over different portions of the BMI distribution two different methods are employed. The first is an IV Quantile regression, which takes the form of Model (3) but allows the estimation of different marginal effects at various points in the BMI distribution. Here estimates are provided at the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles.

The second method used to account for potential non-linearity in the relationship between income and BMI is to construct indicator variables for two clinical weight classifications of interest: overweight (BMI $\geq$ 25); and obese (BMI $\geq$30). Estimates of the relationship between income and the two clinical weight classifications are generated using an IV probit model with each of the clinical weight classifications as the dependent variable. For the IV Probit model, the same first and second stage regressors as Models (1) and (2) are used, respectively.

1.6. Empirical Results

The least squares estimates of the impact of family income on BMI for EITC eligible men are presented in Table 1.8. Results of the OLS model are shown in column 1. They suggest that an additional $1,000 of family income would have a slight negative effect on BMI, decreasing it by 0.008 units. With the introduction of the IVs in column 2, the coefficient on family income becomes positive—though the effect is statistically insignificant. Columns 3 and 4 then present results from the OLS and IV models with the inclusion of the number of hours worked in the previous calendar year as a covariate; columns 5 and 6 include state fixed-effects; and columns 7 and 8 include both hours worked and state fixed-effects. With the inclusion of hours worked and the use of IVs in column 4 an additional $1,000 of family income is now associated with an increase in BMI of 0.05 units. The inclusion of just state fixed-effects in column 6 yields an IV estimate indicating that an additional $1,000 of family income is associated with an increase in BMI of 0.04 units. With both hours worked and state fixed-effects included in the IV model, the coefficient on family income in column 8 suggests that an additional $1,000 of family income is associated with an increase in BMI of 0.07 units. To put this value in perspective, for the average man in the sample whose adjusted height is five feet, nine inches tall, and whose adjusted weight is 198 pounds in 2002, a 0.07 unit change in BMI translates into a change in weight of 0.5 pounds. [8] For men, the effective of family income on BMI is statistically insignificant in all specifications.

[8] The average increase in weight in pounds is backed out using the formula BMI= weight (lb) / [height (in)]^2 x 703 and by plugging in values of in=69 and BMI=0.07.

Table 1.8. Estimates of Adjusted Body Mass Index on Family Income for Men

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable: Adjusted BMI	OLS	IV	OLS	IV	OLS	IV	OLS	IV	IV	IV	IV	IV
Family Income ($1,000s)	-0.0078	0.0304	-0.0022	0.0529	-0.0115	0.0371	-0.0056	0.0693	0.0322	0.1867	0.0529	0.1264
	(0.64)	(0.45)	(0.17)	(0.53)	(1.42)	(0.95)	(0.62)	(1.17)	(0.67)	(0.76)	(1.17)	(0.39)
Number of Hours Worked Past Year			X	X			X	X				
State FEs					X	X	X	X			X	X
Restrict Sample to Working									X		X	
Restrict Sample to Not Working										X		X
Observations	4372	4372	4372	4372	4372	4372	4372	4372	3413	959	3413	959
R-Squared	0.1	0.09	0.1	0.09	0.1	0.08	0.1	0.07	0.11	0.02	0.08	0.06
First-Stage F-Statistic		50.95		33.28		98.14		50.80	65.88	4.21	73.17	2.13

Notes:
(1) Robust t statistics in parentheses. Standard Errors Clustered by State.
(2) Other regressors include: age, age squared, foreign born status, race/ethnicity, marital status, number of own children ever born, number of adults in the household, highest level of education achieved, residence in an MSA, AFQT Score, TANF receipt, Food Stamps receipts, fast food price index, food at home price index, cigarette prices

Columns 9 through 12 of Table 1.8 show results for the effect of family income on BMI when splitting the sample between those working and those not working with and without state fixed-effects. Though family income appears to have a larger effect on the BMI of those who are not working than on those who are working, the difference in coefficients is not statistically significant.

Table 1.9 presents the least squares estimates of the effect of family income on BMI for women. Across all specifications family income has a much larger positive effect on the BMI of women than it did on the BMI of men. In the OLS model, shown in column 1, an additional $1,000 of family income is associated with an increase of 0.03 BMI units. With the introduction of the IVs in column 2, the magnitude of the coefficient on family income increases—indicating that an additional $1,000 of family income is associated with an increase of 0.18 BMI units. As in Table 1.8, columns 3 and 4 of Table 1.9 present results from the OLS and IV models with the inclusion of the number of hours worked in the previous calendar year as a covariate; columns 5 and 6 include state fixed-effects; and columns 7 and 8 include both hours worked and stat fixed-effects. In all specifications the coefficient on family income increases in magnitude with the inclusion of IVs. With the inclusion of hours worked and the use of IVs in column 4 an additional $1,000 of family income is now associated with an increase in BMI of 0.24 units. The inclusion of state fixed-effects in column 6 yields an IV estimate indicating that an additional $1,000 of family income is associated with an increase in BMI of 0.18 units. With both hours worked and state fixed-effects included in the IV model, the coefficient on family income in column 8 suggests that an additional $1,000 of family income is associated with an increase in BMI of 0.24 units, or 1.39 pounds (the average woman in the sample has an adjusted height of five feet, four inches, and an adjusted weight of 174 pounds in 2002 meaning that 0.24 BMI units results in a change in weight of 1.39 pounds).

Table 1.9. Estimates of Adjusted Body Mass Index on Family Income for Women

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable: Adjusted BMI	OLS	IV	OLS	IV	OLS	IV	OLS	IV	IV	IV	IV	IV
Family Income ($1,000s)	0.0348***	0.1834*	0.0272*	0.2354	0.0320***	0.1758***	0.0256**	0.2377**	0.2077***	0.4506	0.1609**	0.7866
	(2.77)	(1.79)	(1.99)	(1.53)	(3.37)	(2.66)	(2.47)	(2.23)	(2.70)	(1.23)	(1.96)	(1.57)
Number of Hours Worked Past Year			X	X			X	X				
State FEs					X	X	X	X			X	X
Restrict Sample to Working									X		X	
Restrict Sample to Not Working										X		X
Observations	7310	7310	7310	7310	7310	7310	7310	7310	5345	2165	5345	2165
R-Squared	0.08	0.05	0.08	0.03	0.08	0.04	0.08	0.02	0.05	0.00	0.06	0.00
First-Stage F-Statistic		46.19		30.37		80.48		37.07	57.51	4.64	48.42	3.11

Notes:
(1) Robust t statistics in parentheses. Standard Errors Clustered by State.
(2) Other regressors include: age, age squared, foreign born status, race/ethnicity, marital status, number of own children ever born, number of adults in the household, highest level of education achieved, residence in an MSA, AFQT Score, TANF receipt, Food Stamps receipts, fast food price index, food at home price index, cigarette prices
(3) * significant at 10%; ** significant at 5%; *** significant at 1%

For women, the IV coefficient estimates on family income are statistically significant in all specifications except #4, which includes only hours worked—owing to the reduction in the first stage F-statistic as a result of the correlation of hours worked with income. The use of IVs yields a significant improvement in the coefficient estimate on family income across specifications for both men and women, as the results of Hausmann tests (not reported here) reject equality between OLS and IV estimates.

To allow for the possibility that the effect of income on BMI varies across the BMI distribution, IV Quantile models were estimated at the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} percentiles. Table 1.10 presents the results of the IV Quantile regressions for men—with and without the inclusion of the number of hours worked—which indicate that the aggregate estimates presented in Table 1.8 do in fact mask important variation in the effect of family income across the BMI distribution. Row 1 presents results without the inclusion of hours worked. Here, an additional $1,000 of family income is associated with: an increase of 0.094 BMI units at the 10^{th} percentile of BMI (22.67 units); an increase of 0.064 BMI units at the 25^{th} percentile of BMI (24.90 units); an increase of 0.085 BMI units at the 50^{th} percentile of BMI (27.79 units); a decrease of 0.001 units at the 75^{th} percentile of BMI (31.70 units); and a decrease of 0.087 units at the 90^{th} percentile of BMI (35.80 units).

With the inclusion of hours worked in row 2, an additional $1,000 of family income is associated with an increase of 0.137 BMI units at the 10^{th} percentile of BMI; an increase of 0.093 BMI units at the 25^{th} percentile of BMI; an increase of 0.12 BMI units at the 50^{th} percentile of BMI; a decrease of 0.016 units at the 75^{th} percentile of BMI; and a decrease of 0.144 units at the 90^{th} percentile of BMI. Translating these coefficient estimates into pounds, the results indicate that the effect of an additional $1,000 in family income on the weight of men varies from increasing weight by one pound at the bottom end of the BMI distribution to decreasing weight by one pound at the top end. However, regardless of whether or not hours worked is included, only the coefficient estimates on family income at the 10^{th} percentile of BMI are statistically significant (and positive).

Table 1.11 presents the IV Quantile estimates for women. Unlike the estimates for men, those for women demonstrate a clear upward trend in the association between family income and BMI across the BMI distribution. Row 1 presents results without the inclusion of hours worked, which show that at the 10^{th} percentile of women's BMI (20.45 units), an additional $1,000 of family income is associated with an increase of 0.052 BMI units, while at the 90^{th} percentile of BMI (37.71 units) an additional $1,000 of family income is associated with an increase of 0.278 BMI units. The magnitude of the coefficient on income increases significantly between the 25^{th} percentile of BMI (23.06 units) and the 50^{th} percentiles of BMI (27.00 units), and the 75^{th} percentile of BMI (32.44 units) and the 90^{th} percentile of BMI. From the 25^{th} to 50^{th} percentile, the effect of an additional $1,000 in family income on BMI nearly doubles, going from increasing BMI by 0.098 units to increasing BMI by 0.182 units. Between the 75^{th} percentile of BMI and the 90^{th} percentile of BMI, the effect of an additional $1,000 in family income on BMI increases by more than 0.10 BMI units, going from increasing BMI by 0.1637 units to increasing BMI by 0.278 units.

Table 1.10. Adjusted Body Mass Index IV Quantile Estimates for Men

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Adjusted BMI	10th Percentile	25th Percentile	50th Percentile	75th Percentile	90th Percentile
Family Income ($1,000s)	0.0935*	0.0637	0.0848	-0.0007	-0.0873
	(1.82)	(1.31)	(1.52)	(0.01)	(1.25)
Family Income ($1,000s): with Hours Worked	0.1372*	0.0929	0.1204	-0.0161	-0.1443
	(1.73)	(1.25)	(1.52)	(0.14)	(1.40)
Observations	4372	4372	4372	4372	4372

Notes:
(1) t statistics in parentheses derived from Bootstrapped standard errors
(2) Other regressors include: age, age squared, foreign born status, race/ethnicity, marital status, number of own children ever born, number of adults in the household, highest level of education achieved, residence in an MSA, AFQT Score, TANF receipt, Food Stamps receipts, fast food price index, food at home price index, cigarette prices
(3) * significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.11. Adjusted Body Mass Index IV Quantile Estimates for Women

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Adjusted BMI	10th Percentile	25th Percentile	50th Percentile	75th Percentile	90th Percentile
Family Income ($1,000s)	0.0523	0.0981	0.1824**	0.1636	0.2776*
	(0.96)	(1.43)	(2.57)	(1.47)	(1.72)
Family Income ($1,000s): with Hours Worked	0.0411	0.0659	0.2164*	0.2063	0.4281*
	(0.42)	(0.65)	(1.79)	(1.11)	(1.67)
Observations	7310	7310	7310	7310	7310

Notes:
(1) t statistics in parentheses derived from Bootstrapped standard errors
(2) Other regressors include: age, age squared, foreign born status, race/ethnicity, marital status, number of own children ever born, number of adults in the household, highest level of education achieved, residence in an MSA, AFQT Score, TANF receipt, Food Stamps receipts, fast food price index, food at home price index, cigarette prices
(3) * significant at 10%; ** significant at 5%; *** significant at 1%

With the inclusion of hours worked to the model in row 2 of Table 1.11 the magnitude of the coefficient decreases for those at the 10th and 25th percentile of BMI and increases for those at or above the 50th percentile. Here, an additional $1,000 of family income is associated with an increase of 0.041 BMI units at the 10th percentile of BMI; an increase of 0.066 BMI at the 25th percentile of BMI; an increase of 0.216 BMI units at the 50th percentile; an increase of 0.206 BMI units at the 75th percentile; and an increase of 0.428 units at the 90th percentile of BMI. These results indicate that for women the effect of income on BMI is largest for those who are already overweight or obese. The coefficient estimates for women in the IV model are statistically significant at the 50th and 90th percentiles of BMI.

As an additional means of examining the possibility that the impact of family income varies over the range of BMI, Probit and IV Probit models of the effect of family income on the binary dependent variables overweight and obese are estimated, with the results presented in Tables 1.12 and 1.13.[9] Probit models are used as opposed to linear probability models, as they are the preferred method of estimating models with binary dependent variables (Maddale, 1983).

Columns 1 and 2 of Table 1.12 present standard probit and IV Probit results, respectively, for the effect of income on the probability of being overweight for men, while columns 3 and 4 add the number of hours worked to the model. The standard Probit model indicates that an additional $1,000 in family income is associated with a 0.06 percent decrease in the probability of being overweight, while the IV estimate indicates that an additional $1,000 in family income increases the probability of being overweight by 0.24 percent. The addition of hours worked to the model yields similar results, with the standard Probit model indicating that an additional $1,000 in family income is associated with a 0.05 percent decrease in the probability of being

[9] The overweight classification includes those in the obese category as it covers all individuals with a BMI ≥ 25.

overweight, while the IV estimate indicate that an additional $1,000 in family income increases the probability of being overweight by 0.44 percent.

Columns 5 through 8 of Table 1.12 then present the corresponding results for the dependent variable obese. Again, the standard Probit model finds a negative relationship between family income and the probability of being obese, while the IV estimate indicates a positive relationship between family income and the probability of being obese. As with most of the previous estimates for men, none of the IV effects of family income on clinical weight classification are statistically significant.

Table 1.13 presents the Probit estimates for women. Similar to the OLS estimates of the effect of family income on BMI, the IV results show significant increases in the magnitude of the effect of family income on both the probability of being overweight and the probability of being obese, relative to the standard estimates. Column 1 presents the standard Probit estimate, which indicates that an additional $1,000 in family income increases the probability of being overweight by 0.23 percent. With the use of the IV Probit in column 2 the coefficient on family income increases in magnitude and now indicates that an additional $1,000 in family income increases the probability of being overweight by 0.71 percent. With the inclusion of hours worked the IV Probit model yields an even larger effect, with an additional $1,000 in family income increasing the probability of being overweight by 0.84 percent.

Results for obesity are presented in columns 5 through 8 of Table 1.13. As with overweight, the standard Probit model yields significantly lower estimates of the effect of family income on the probability of being obese. In columns 5 and 6, the effect of an additional $1,000 in family income goes from increasing the probability of being obese by 0.16 percent in the standard Probit model to increasing the probability of being obese by 1.27 percent in the IV Probit model, while in columns 7 and 8, which include hours worked, the effect of an additional $1,000 in family income goes from increasing the probability of being obese by 0.11 percent to increasing the probability of being obese by 1.67 percent. The IV coefficient estimates on family income are significant at the 5 percent level with or without the inclusion of hours worked.

1.7. Conclusions

The results presented in this paper indicate that correlational estimates of the impact of income on weight are strongly biased downward. For both men and women, and across all models and specifications, the standard estimates suggested a much smaller effect of family income on weight than the estimates produced using IVs. In response to the theoretical predictions presented in Lakdawalla and Philipson (2002) regarding differential effects for labor and non-labor income on weight, this paper estimated models with family income as a whole, as well as split between labor and non-labor income. Moreover, the number of hours of worked was included and then excluded in an attempt to capture the effect of work on weight. This produced no significant change in the estimates. Lastly, separate estimates for those working and not working were produced; again yielding no significant difference in the coefficient on family income. This paper provides robust evidence of a positive causal link between income and weight for women; however, no statistically significant relationship between income and weight is found for men.

Using the exogenous variation in family income obtained from the correlation of their family income with differences in the level of the state EITC supplement at a point in time and variations in the value of federal and state EITC benefits over time, I find that additional family income significantly raises the BMI of women eligible for the EITC, while for men a small positive, though insignificant, relationship is found.

For women an additional $1,000 is associated with an increase in BMI of as much as 0.24 units, or an average of 1.4 pounds of weight, while for men, an additional $1,000 of family income is associated with an increase in BMI of as much as 0.07 units or an average of 0.5 pounds of weight in the IV specification which includes hours worked and state fixed-effects.

As the average real family income in my sample increased from $17,387 in 1989 to $18,032 in 2001 for men, and from $16,860 in 1989 to $18,533 in 2002 for women, these IV coefficient estimates imply that rising family incomes resulted in an average increase in BMI of 0.05 units (0.33 pounds) for men and 0.40 units (2.33 pounds) for women. As shown in Table 1.5 average adjusted BMI increased by 1.90 units for men and 2.73 units for women from 1990 to 2002. Therefore my results indicate that increased income is responsible for 3 percent of the increase in BMI for the men in my sample and 15 percent of the increase in BMI for the women in my sample.

This paper's estimation of the effect of family income on BMI at different points in the BMI distribution using an IV Quantile model yields results that suggest that, at least for women, the effect of income on weight is greatest for those who are already either overweight or obese. Moreover, the results for women from the probit model suggest that increasing family income significantly increases the prevalence of overweight and obese. The increased prevalence of overweight and obese is particularly troubling from a public health perspective, as Calle et al. (1999) shows that for women age 30 to 64 going from a healthy weight (BMI between 20.5 and 24.9) to overweight (BMI between 25 and 29.9) increases mortality by approximately 33 percent, and that going from overweight to marginally obese (BMI between 30.0 and 31.9) increases mortality by 14 percent.

Table 1.12. Probit Estimates of Overweight and Obese for Men

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	Overweight				Obese			
	Probit	IV	Probit	IV	Probit	IV	Probit	IV
Family Income ($1,000s)	0.0062***	0.0189	-0.0019	0.0077	-0.0034	0.0127	-0.0031	0.0202
	(2.65)	(0.98)	(0.58)	(0.40)	(1.04)	(0.82)	(1.08)	(0.98)
	[-0.0006]	[0.0024]	[-0.0005]	[0.0044]	[-0.0012]	[0.0047]	[-0.0011]	[0.074]
Number of Hours Worked Past Year			**X**	**X**			**X**	**X**
Observations	4372	4372	4372	4372	4372	4372	4372	4372
First-Stage F-Statistic		50.95		33.28		50.95		33.28

Notes:
(1) Robust t statistics in parentheses. Standard Errors Clustered by State.
(2) Marginal effects in brackets.
(3) Other regressors include: age, age squared, foreign born status, race/ethnicity, marital status, number of own children ever born, number of adults in the household, highest level of education achieved, residence in an MSA, AFQT Score, TANF receipt, Food Stamps receipts, fast food price index, food at home price index, cigarette prices
(4) * significant at 10%; ** significant at 5%; *** significant at 1%

Table 1.13. Probit Estimates of Overweight and Obese for Women

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	Overweight				Obese			
	Probit	IV	Probit	IV	Probit	IV	Probit	IV
Family Income ($1,000s)	0.0062***	0.0189	0.0046*	0.0222	0.0043**	0.0346**	0.003	0.0451**
	(2.65)	(0.98)	(1.88)	(0.86)	(2.18)	(2.51)	(1.22)	(1.99)
	[0.0023]	[0.0071]	[0.0017]	[0.0084]	[0.0016]	[0.0127]	[0.0011]	[0.0167]
Number of Hours Worked Past Year			X	X			X	X
Observations	7310	7310	7310	7310	7310	7310	7310	7310
First-Stage F-Statistic		46.19		30.37		46.19		30.37

Notes:
(1) Robust t statistics in parentheses. Standard Errors Clustered by State.
(2) Marginal effects in brackets.
(3) Other regressors include: age, age squared, foreign born status, race/ethnicity, marital status, number of own children ever born, number of adults in the household, highest level of education achieved, residence in an MSA, AFQT Score, TANF receipt, Food Stamps receipts, fast food price index, food at home price index, cigarette prices
(4) * significant at 10%; ** significant at 5%; *** significant at 1%

Based on the IV Quantile regression results, the majority of the effect of family income on BMI appears to be driven by those women who are already classified as overweight or obese. These results suggest that additional income mainly serves to increase the weight of those already overweight and obese. Thus, the need exists for continued research into what income fueled activity is driving increases in weight: increased food consumption and poor nutritional choices or increased sedentary activities.

Unfortunately, my choice of IV limits the broad generalizability of the results presented here. However, given that the instrument used, eligibility for the Earned Income Tax Credit, applies to 22 million low-income families, or 16.6 percent of all individual income tax returns, the results are applicable to a large swath of the American population, and certainly to those with the greatest prevalence of overweight and obese.

This paper opens numerous avenues of future research. Most immediately, the methods used here could be extended to estimating the effect of family income on the BMI of children using the Children of the NLSY79 dataset. Secondly, the strength of the EITC as an instrument for income opens up the possibility of exploring causal relationships between income and numerous outcomes previously plagued by endogeneity and reverse causality. Lastly, given that no papers examining the determinants of the rise of obesity in the U.S. have accounted for the endogeneity and reverse causality between income and BMI, future research in this area could make use of the EITC as an instrument and improve the estimates of the causes of the obesity epidemic.

APPENDIX

1.8. Labor Supply Effects of the Earned Income Tax Credit Program

1.8.1. Design of the program

Table 1.1 details the EITC parameters for Tax Year 2007. For a single childless individual, a credit rate of 7.65 percent is applied to the first $5,590 in labor earnings for a maximum benefit of $428. For family with one child, a credit rate of 34 percent is applied to earnings up to $8,390, for a maximum benefit of $2,853, while for a family with two or more children a credit rate of 40 percent is applied to earnings up to $11,790, for a maximum benefit of $4,716. Beginning at earnings of $7,000 for single childless individual and $15,390 for both families with one eligible child and families with two or more eligible children the maximum benefits are reduced at a rate of 7.65 percent, 15.98 percent, and 21.06 percent, respectively. Federal EITC benefits are completely phased out at $12,590 for single childless individuals, $33,241 for families with one eligible child, and $37,783 for families with two or more children eligible children. For those married filling jointly, the breakeven point is extended by $2000 in an attempt to partially offset the disincentive to marriage.

1.8.2. Theoretical Effects on Labor Supply

Labor supply models based on microeconomic theory assume that workers have a fixed amount of time which they divide between work and leisure in order to maximize their utility. Workers derive utility from the goods that can be purchased with their labor earnings and directly from their leisure time. Potential workers have a reservation wage (level of compensation) below which they will not work at all as the utility derived from the potential labor earnings does not exceed the utility derived from allocating those hours to leisure. However, once the offered wage exceeds their reservation wage they will work, but the number of hours they will work depends on the wage rate offered. Hence, the theoretical effect of the EITC on the decision to work for unmarried individuals is unambiguously positive. Because the EITC unambiguously raises the offer wage it can only increase the likelihood that an eligible person will enter the labor market and agree to work. However, the availability of the EITC to married people results in less obvious overall employment outcomes. While the worker taking advantage of the EITC may enter the workforce, the increased income this brings to the family could reduce the employment of other family members since, if leisure is a normal good (more of it is demanded as income increases), this increased income could lead to another earner in the family reducing overall hours worked and possibly leaving the labor force (Ellwood, 2001).

The effect of the EITC on hours worked for those already in the labor force is more ambiguous. Microeconomic theory argues that if the EITC changes the value of an additional hour of work, it will also change the income associated with that additional hour of work. The change in the value of an additional hour of work is referred to as the "substitution" effect and it implies that if workers receive a higher return from an additional hour of work they will choose to work more and reduce their leisure time, all else equal. However, a change in the income associated with that additional hour of work is referred to as the "income effect" and, assuming that leisure is a normal good, an increase in compensation will result in workers working less and taking more leisure.

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CHAPTER TWO:
EXPANDING NEW YORK STATE'S EARNED INCOME TAX CREDIT PROGRAM: THE EFFECT ON WORK, INCOME, AND POVERTY

Abstract

Given its favorable employment incentives and ability to target the working poor, the Earned Income Tax Credit (EITC) has become the primary anti-poverty program at both the federal and state level. However, when evaluating the effect of EITC programs on income and poverty, governments generally calculate the effect using simple accounting, where the value of the state and/or federal EITC benefit is added to a person's observed income. These calculations omit the behavioral incentives created by the existence of these programs, the corresponding effect on labor supply and hours worked, and therefore the actual effect on income and poverty. Using data from the 2005 Current Population Annual Social and Economic Supplement and labor supply parameters drawn from the labor economics and EITC literature, this paper simulates the effect of an expansion of the New York State EITC benefit on employment, hours worked, income, poverty, and program expenditures for those both currently in the labor force, and those not currently in the labor force. These results are then compared to those omitting labor supply effects. Relative to estimates excluding labor supply effects, the preferred behavioral results show that an expansion of the New York State EITC increases employment by an additional 14,244 persons, labor earnings by an additional \$95.8 million, family income by an additional \$84.5 million, decreases poverty by an additional 56,576 persons, and increases costs to the State by \$29.7 million.

JEL classifications: H24; J2; J38

Keywords: Poverty; EITC; Labor Supply

2.1. Introduction

The federal Earned Income Tax Credit (EITC) is the nation's largest anti-poverty program for non-elderly individuals and is responsible for lifting millions of working families out of poverty (Meyer and Holtz-Eakin, 2001). For tax year 2004 the federal EITC program disbursed $39.2 billion[1] to over 21 million low-income workers (Center on Budget and Policy Priorities, 2007). In addition to the federal EITC, as of January 2006, 19 states and the District of Columbia operate their own supplemental EITC programs. The value of a taxpayer's state EITC is generally set as a fraction of their federal EITC.[2] The state credits vary significantly in terms of their generosity relative to the federal EITC, and not all are refundable.[3]

New York State was an early implementer of a state EITC program and offers one of the largest fully refundable supplemental credits in the nation. Initially set at 7.5 percent of the federal credit in 1994, the New York State supplement to the Federal EITC has been raised six times since then, reaching 30 percent of the federal EITC in 2003. In Tax Year 2004, 1.3 million New York State families received almost $670 million in state EITC credits, making it the largest state EITC in the Nation in terms of the total value of tax credits provided (New York State Department of Taxation and Finance, 2005).

When evaluating the effect of both state and federal EITC programs on income and poverty, policy makers generally calculate the effect using simple accounting, whereby the value of the state and/or federal EITC benefit is simply added to a persons observed income. For example, this procedure is used by the Census Bureau in the calculation of its Alternative Poverty Rates, and also by the Congressional

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[1] Unless otherwise noted, all figures are in 2004 dollars.
[2] Minnesota's EITC is not linked to the Federal EITC program.
[3] As of January 2006, State EITC programs exist in: Colorado; Delaware; D.C.; Illinois; Indiana; Iowa; Kansas; Maine; Maryland; Massachusetts; Minnesota; New England; New Jersey; New York; Oklahoma; Oregon; Rhode Island; Vermont; Virginia; and Wisconsin.

Research Service for the House Ways and Means Committee Green Book. However, by simply adding the value of the EITC benefits to income, these calculations omit the behavioral incentives created by the existence of these programs, the corresponding effect on labor supply and hours worked, and therefore income and poverty. As such, these types of estimates do not accurately capture the full effect of EITC programs on work, income, and poverty rates.

While numerous studies have evaluated the labor supply effects of the federal EITC[4] only a handful (Holtzblatt et al., 1994; Browning, 1995; Scholz, 1996) have simulated the net of labor supply behavior effect on employment and hours worked of a potential future increase in the federal EITC. No previous study has simulated the effect of an increase in a state supplement on employment or hours worked, nor have they extended their simulation to estimating the effect on poverty rates. This study simulates the effect—including labor supply behavior—of an expansion of the New York State EITC supplement on employment, hours worked, income, and poverty using data from the 2005 Current Population Survey (CPS) Annual Social and Economic Supplement (ASEC), which covers tax year 2004. The simulation starts from the current 30 percent New York State Supplement to the Federal EITC and increases the value of the supplement in increments of 5 percentage points to 35 percent, 40 percent, and 45 percent of the Federal EITC benefit. This study contributes to the existing literature by extending the simulation of EITC expansion outcomes to income and poverty rates—two outcomes of immense interest to policymakers—and by providing a framework for states to simulate the introduction or expansion of a supplemental EITC program.

[4] See Hotz and Scholz (2003) for a review of papers examining the labor supply effects of the EITC.

2.2. Background

2.2.1. Background on the Federal EITC

Originally enacted in 1975 to offset the payroll taxes of workers with low earnings, the Federal EITC was expanded in scope and size in 1986, 1990 and most recently in 1993. Available only to those with labor earnings, the EITC acts as a wage subsidy, providing an incentive for those not working to enter the labor force. It also supplements the income of those who, despite their work effort, have low labor earnings.

There are three distinct earnings ranges to this labor earnings-based tax credit (see Figure 2.1). Total benefits rise during the phase-in range of the credit, reaching the maximum benefit level for families with eligible children near the poverty threshold for a family of three. At some labor earnings level, called the plateau range, no new benefits are earned as labor earnings increase, but the credit is not reduced. At a still higher level of labor earnings, the phase-out range begins and total benefits fall with additional earnings. This continues until EITC benefits decline to zero; the breakeven point is reached. The EITC was designed with these three distinct regions in order to largely avoid the work disincentives present in other means tested programs in which benefits are reduced for every dollar earned.

Table 2.1 presents the Federal EITC parameters for tax year 2004. For a family with one child, a credit rate of 34 percent is applied to earnings up to $7,660, for a maximum credit of $2,604, while for a family with two or more children a credit rate of 40 percent is applied to labor earnings up to $10,750, for a maximum credit of $4,300. Single individuals receive a credit of 7.65 percent on earnings up to $5,100 for a maximum credit of $390. The phase-out of the credit begins at earnings of $6,390 for a single individual and $14,040 for families with children. With benefits reduced at a rate of 7.65 percent, 15.98 percent, and 21.06 percent, respectively, the Federal

EITC breakeven points are $11,750 for single individuals; $31,030 for families with one eligible child; and $35,263 for families with two or more eligible children. For those married filing jointly, the plateau and breakeven point is extended by $2,000 in an attempt to partially offset the disincentive to marriage. The long range over which the EITC benefit plateaus and is phased-out means that besides helping families to escape poverty, the EITC helps to boost the income of a large number of working families that earn above the poverty level but still have low incomes.

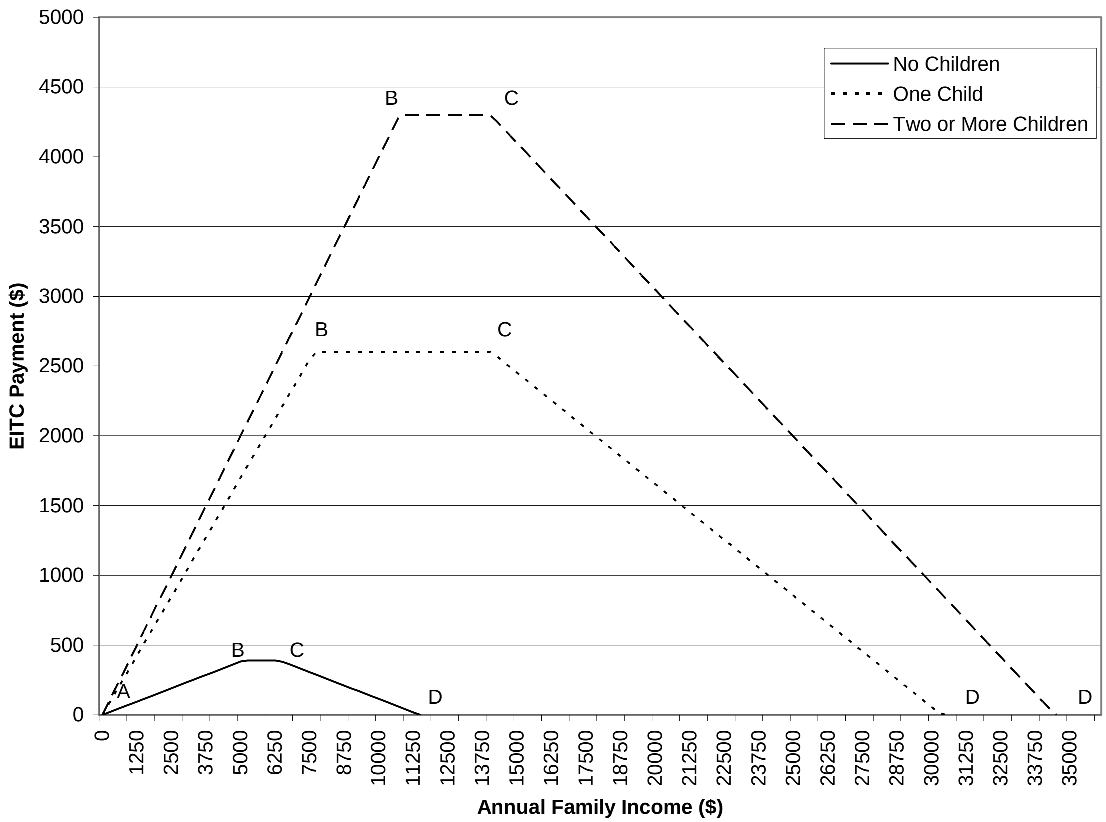

Figure 2.1. Federal EITC Schedule 2004. Source: Internal Revenue Service (Downloaded March 2005 from http://www.irs.gov/pub/irs-drop/rp-03-85.pdf)

Table 2.1. 2004 Federal Earned Income Tax Credit Parameters

Type of Return	Maximum Eligible Earnings	Maximum Credit	Begin Phase-out	Breakeven Point	Credit Rate	Phase-out Rate
Childless	$5,100	$390	$6,390	$11,490	7.65%	7.65%
1 Child	$7,660	$2,604	$14,040	$30,338	34.00%	15.98%
2 or More Children	$10,750	$4,300	$14,040	$34,458	40.00%	21.06%

Note: Married Filing Jointly have Phase-out and Breakeven points $1,000 above listed values.
Source: Downloaded March 2005 from http://www.irs.gov/pub/irs-drop/rp-03-85.pdf

Results of a wide range of studies evaluating past expansions using a variety of econometric techniques show that the Earned Income Tax Credit is effective at increasing employment rates of low-wage workers (Leibman, 1998; Eissa and Leibman, 1996; Meyer and Rosenbaum, 1999; Holtz, Mullin and Scholz, 2006), and that previous expansions of the EITC have reduced the poverty rates of children and families (Blank and Schoeni, 2000). The effect of the EITC on poverty has also been demonstrated by simply adding the credit to family income and calculating the difference this makes in the number of poor. Each year, the Census Bureau provides estimates of this type—called the Alternative Measures of Income and Poverty—for the U.S. based on data from the CPS; other researchers (e.g., Meyer and Holtz-Eakin, 2001) and organizations estimate the effects in this way from other data sources as well as from the CPS.

2.2.2 Background on the New York State EITC Supplement

The New York State supplement to the Earned Income Tax Credit (NYS EITC) was enacted in 1994. Designed as a fixed percent of the Federal credit for single individuals and for families, New York State’s credit, like the Federal credit, is totally refundable. Initially set at 7.5 percent of the Federal credit, the NYS EITC has been raised six times, reaching 30 percent of the Federal credit in 2003.

Figure 2.2 shows the amount of the NYS EITC benefit for single individuals and families at different labor earning levels. As noted above, the NYS EITC follows the design of the federal credit, with phase-in, plateau, and phase-out regions set at the same earning levels as the Federal EITC. Figure 2.3 shows the NYS and Federal EITC for a single parent with two children, as well as the combined credit received by such families. The addition of the NYS EITC increases the maximum benefit for a single parent with two or more children by $1,290, from $4,300 to $5,590.

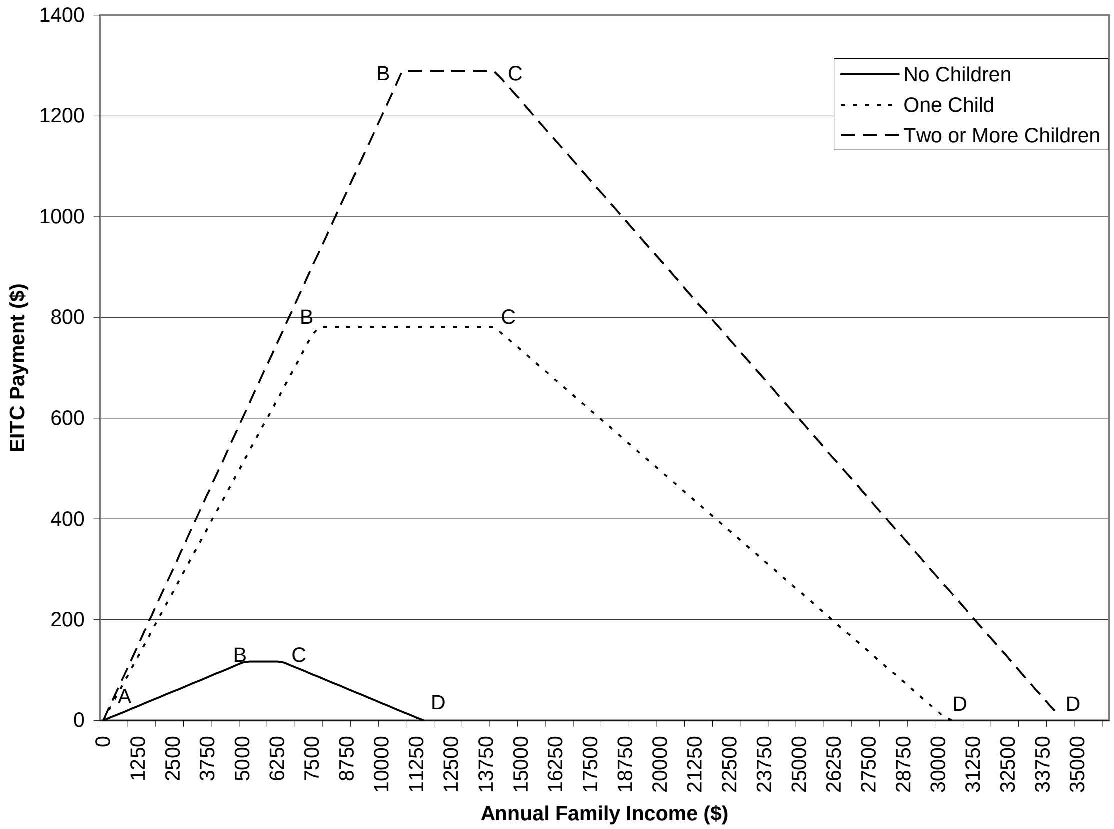

Figure 2.2. New York State EITC Schedule 2004. Source: New York State Department of Taxation and Finance (2005)

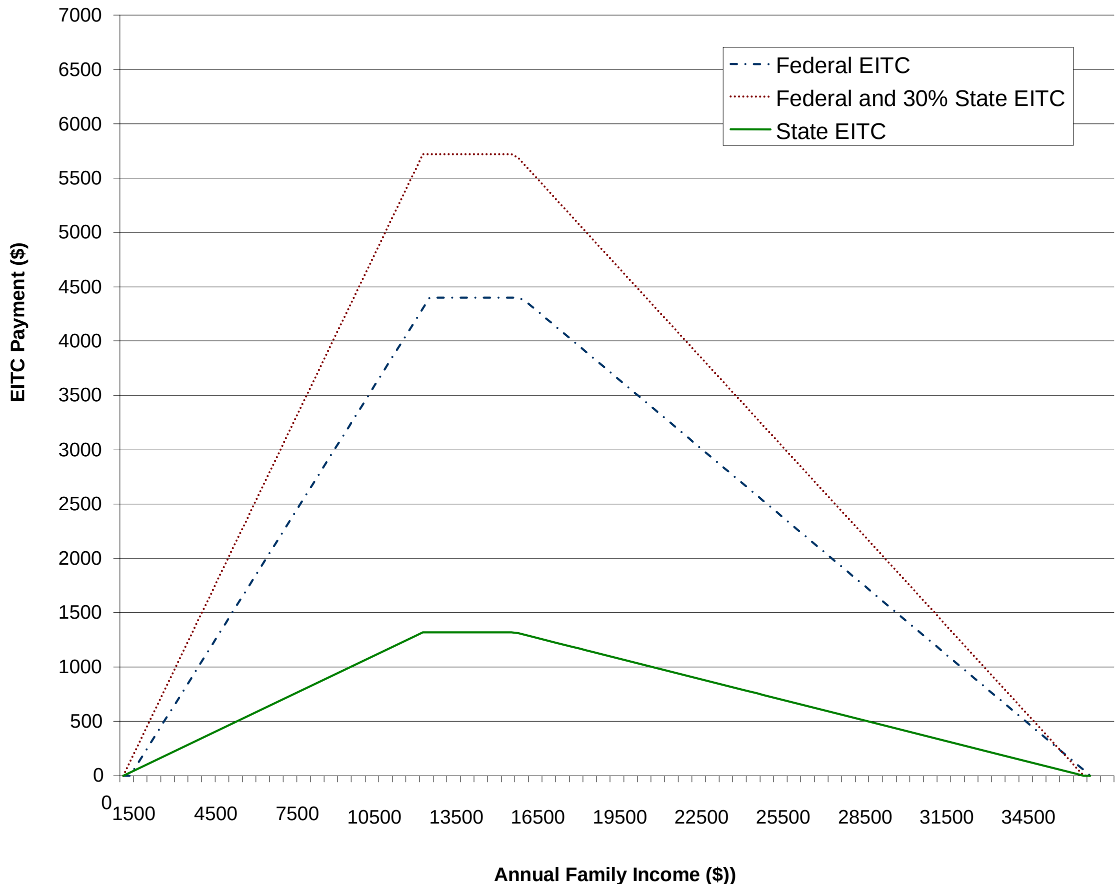

Figure 2.3. Combined New York State and Federal EITC: Single Parent with Two Children

In 2004, 1.3 million New York State families received almost $670 million in NYS EITC benefits, making it the most generous state EITC in the nation in terms of the total amount of tax credits claimed and second only to Vermont in the tax credit provided per family.[5] Figures 2.4 and 2.5 show the total NYS EITC claimants and the dollar value of the total NYS EITC credits.

[5] As of January 2006 19 states and the District of Columbia had an earned income tax credit. At 32 percent of the federal credit, only Vermont has a higher, refundable credit that is fully linked to the federal credit, i.e., is a constant fraction of the Federal credit for all family types.

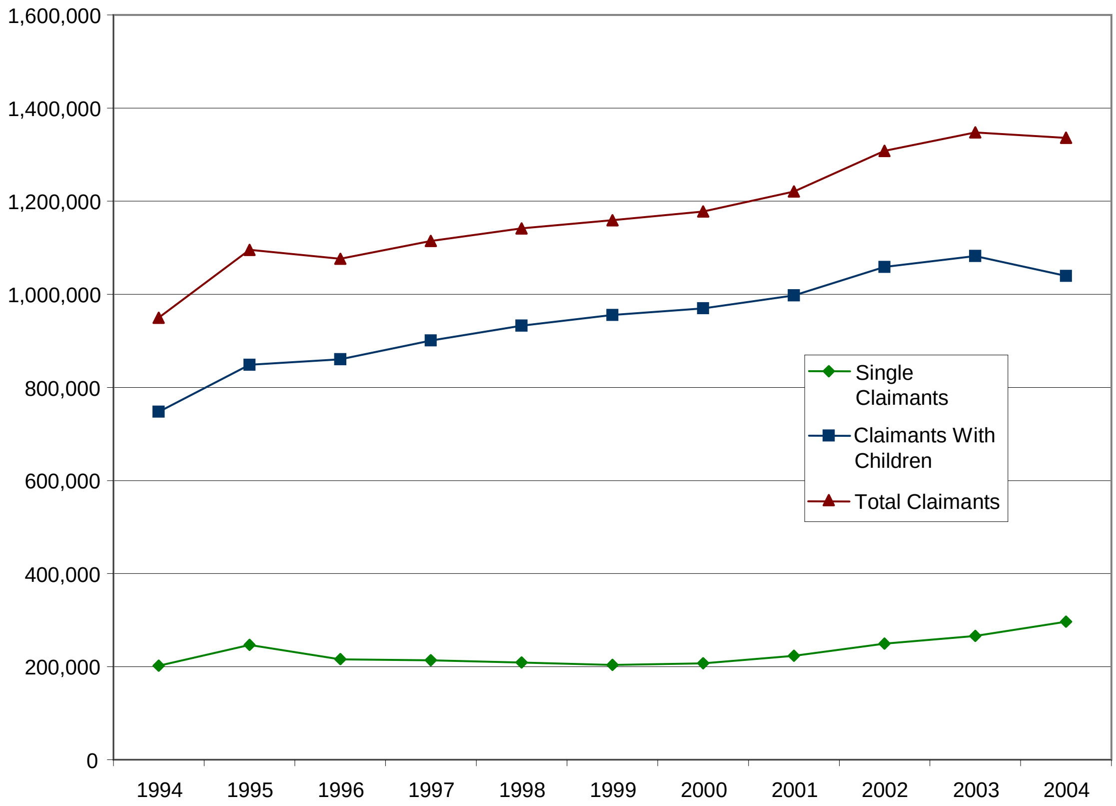

Figure 2.4. New York State EITC Claimants. Source: New York State Department of Taxation and Finance (2005)

Since the inception of the program, the number of claimants with eligible children rose steadily, reaching more than a million New York State families with children in 2002 (see Figure 2.4). The total credits granted increased far more rapidly than claimants—reaching almost $700 million in 2003 (2003 dollars). The rapid rise in total credits was the result of a number of factors, most importantly the fourfold increase in the New York State credit from 7.5 percent to 30 percent of the Federal credit, and the rising number of eligible working families. Adjustments to the Federal credit—including extensions of the plateau and phase-out range for married couples, and parameter increases to adjust for inflation—also contributed to the increase in total State credits.

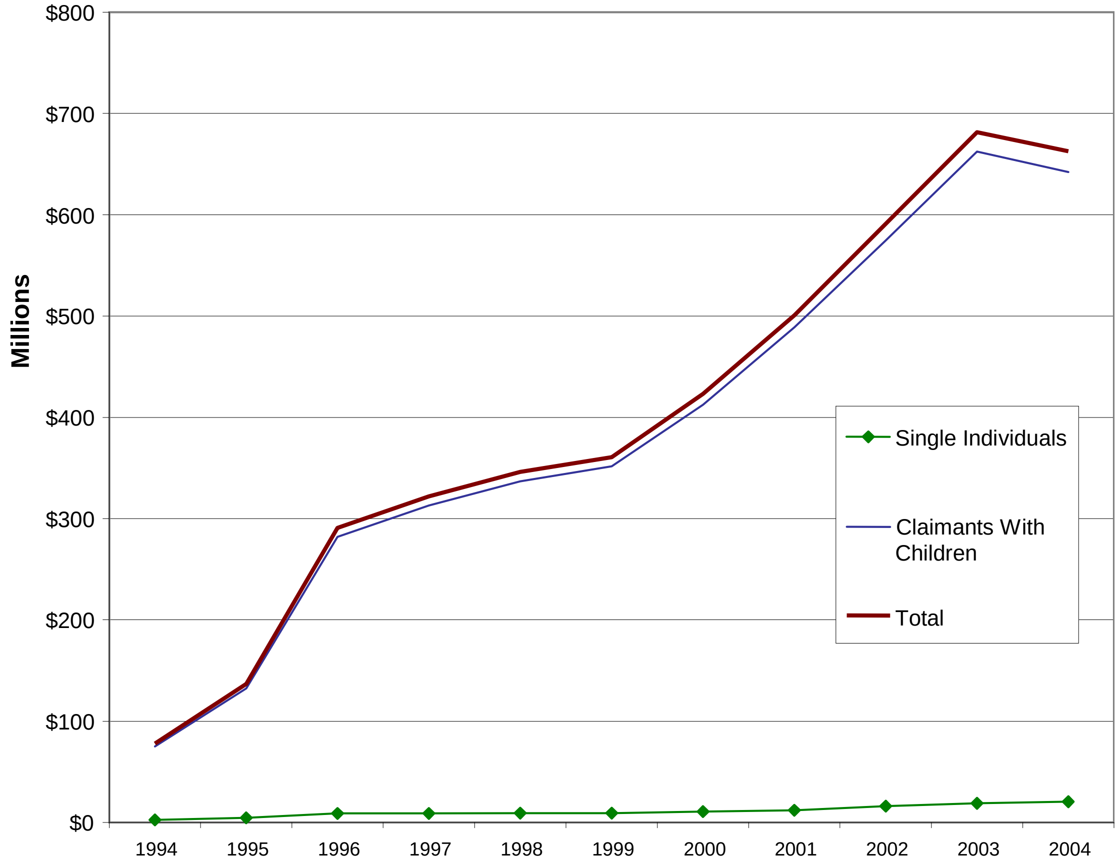

Figure 2.5. Total Credits: New York State Earned Income Tax Credit: 1994-2004. Source: New York State Department of Taxation and Finance (2005)

As the EITC has been shown to increase employment and labor earnings, and decrease poverty, an expansion of the EITC presents a politically and fiscally attractive method of reducing poverty rates. Any state looking to increase the incomes of low-income families and reduce poverty should first consider implementing an EITC supplement, or expanding their existing EITC supplement. The methods outlined here present a straightforward method of incorporating the behavioral labor supply incentives created by the EITC program into an assessment of the costs and benefits of utilizing the EITC program to increase employment and income, and reduce poverty.

2.3. Literature Review

In order to simulate an expansion of the NYS EITC, information is required on the extent to which an EITC increase results in non-employed people entering the labor market as well as the extent to which those already employed change their hours worked. The existing empirical literature on the impact of the EITC on employment has generated numerous estimates of the elasticity of labor force participation (LFP) to net income, which can be used to simulate the number of people entering into the labor market for a given change in net income. As a simplifying assumption for the simulation, all persons who enter the labor force are assumed to become employed.

Simulating the change in hours worked for those already employed is significantly more complicated, since it requires information on both the substitution (as measured by the uncompensated wage elasticity for a given change in the EITC) and income (as measured by the income elasticity for a given change in the EITC) effects of a change in the price of labor caused by a change in the marginal tax rate, and because the change in marginal tax rate varies over the three EITC regions. Though some of the existing empirical literature on the EITC has calculated the net change in hours worked after previous expansions of the EITC, these estimates can not directly be used to simulate future changes to the EITC. Instead, simulating the change in hours worked requires using estimates of the substitution effect and the income effect from the labor supply literature as done in GAO (1993), and Scholz (1996). The remainder of this section serves to describe the simulation method employed by Scholz (1996) in detail, as well as surveys the other studies' estimates of the elasticity of LFP to net income, and the change in hours worked caused by previous expansions of the EITC.

Scholz (1996) simulates the change in annual hours worked effected by the 1996 expansion of the EITC using substitution and income elasticities estimated by

MaCurdy et al. (1990), Triest (1990), and Hausman (1981) as his lower-bound, preferred, and upper-bound estimates, respectively. He first estimates the value of the EITC that each family in his sample from the 1990 Survey of Income and Program Participation (SIPP) would receive in 1993 and 1996. The change in net wages, holding constant all taxes except the EITC, and the change in virtual income is then calculated for each family.[6] He uses these three elasticities to simulate how program changes on net wages and virtual income, respectively, impact hours worked within each region of the EITC.

Scholz (1996)'s preferred simulation results, using the Triest (1990) specifications, for those who were working at the time of the 1996 expansion of the EITC were that those in the phase-in range increase their hours worked by 4 percent; those in the plateau reduce their hours by 0.2 percent; and those in the phase-out region reduce their hours by 1.1 percent. But because significantly more people were in the plateau and phase-out regions, he found that total hours of work fell by 54.5 million.

However this decline in hours worked by those who were employed was more than offset by the movement into employment of those who were not employed at the time of the 1996 expansion. Scholz (1996) estimated that net labor earnings of single parents not in the labor market at the time of the 1996 expansion would increase by 15 percent. This increased overall labor force participation of single parents from 65.5 percent before the change to 72.1 percent after the change. One can not directly obtain an elasticity of LFP with respect to net income from the information provided in Scholz (1996). However, Hotz and Scholz (2003), which reviews the literature on the

[6] Virtual income is the sum of non-earned income and the implicit lump sum subsidy generated by a progressive tax system, which is equal to the difference between the taxes an individual would pay if they faced their marginal tax rate over the full range of their taxable income and the amount of tax they actually pay (Triest, 1993 pp.3-4).

EITC including the Scholz (1996) paper, does so.[7] Based on that information, the value would be approximately 1.46.[8]

Scholz (1996) assumed that new labor market entrants, whether single parents or a parent in a two-parent family, would work an average of 20 hours a week for 20 weeks a year. Thus, he found they provided 145 million new hours of work in the labor market. Thus these added hours more than offset the decrease in hours of those already in the work force, so that total hours worked based on Scholz's best estimates increased by 90.5 million hours.

As mentioned above, the analysis of the impact of the EITC must be separated into an analysis of its impact on those in the labor force and those not currently in the labor force. While Scholz (1996) provides a framework for the analysis of those currently in the labor force, providing a range of estimates for those not currently in the labor force requires several estimates of the elasticity of labor force participation to net income. One often used estimate of the elasticity of labor force participation to net income comes from Eissa and Liebman (1996), who use data for the years 1985 to 1987 and 1989 to 1991 from the March supplement to the CPS to estimate the effects of the 1986 EITC expansion on labor supply. The authors estimate a difference-in-difference model of the labor supply response of single women with children, relative to a control group of all unmarried females without children. As a test of robustness, they also estimate the change in the labor supply response for women with children, with and without a high school education, relative to women without children, with and without a high school education, respectively. The difference-in-difference results suggest the 1987 expansion of the EITC resulted in an increase in the labor force

[7] To calculate elasticities of labor force participation to net income, Hotz and Scholz (2003) use average tax changes as reported in Meyer and Rosenbaum (1999, appendix table 1), average wages from the respective papers, and average hours worked for single women from Eissa and Liebman (1996).
[8] Scholz (1996) estimated that the labor force participation of persons in two-parent families who were not employed at the time of the 1996 expansion only increased by 0.4 percentage points.

participation of single women with children of 2.4 percentage points relative to the aggregate and with high school control groups, and a 4.1 percentage point increase using the less than high school control group, implying an elasticity of LFP to net income of 1.16 (Hotz and Scholz, 2003). Eissa and Liebman then estimate a probit model for labor force participation, and find that the 1987 expansion of the EITC increased the probability of participation by eligible women by 1.9 percentage points. The authors also estimated the change in hours worked resulting from the expansion of the EITC, and find a statistically insignificant effect.[9]

Another estimate of the elasticity of labor force participation to net income comes from Keane and Moffitt (1998). Using data from the fourth wave of the 1994 SIPP, Keane and Moffitt (1998) estimate a structural model of labor supply and participation in programs such as the EITC, food stamps, and AFDC for single women with children. Examining the changes in the EITC program over the period 1984 to 1996 they estimate that the EITC increased the labor force participation of single women with children from 65.4 percent to 76.1 percent; implying an elasticity of labor force participation to employment of approximately 0.96 (Hotz and Scholz, 2003).

Meyer and Rosenbaum (2001) use data from the 1985 to 1997 March supplement to the CPS, as well as the 1984 to 1996 monthly outgoing rotation group, to estimate the impact of the tenfold increase in EITC benefits between 1984 and 1996 in the employment of single mothers. The authors use difference-in-difference methods to compare the employment of single women with children to single women without children. They also estimate a structural model of employment, which exploits cross-state and family type variation in tax and program treatment. The authors

[9] This is a somewhat surprising finding given the labor supply parameters estimated by MaCurdy et al. (1990), Triest (1990), and Hausman (1981). One possible explanation is that at the time the Federal EITC benefit was still a new and relatively small program so that its net effect was more difficult to capture empirically. Alternatively, it may be that its potential beneficiaries were less familiar with the structure of the program and less responsive to its incentives.

conclude that the EITC expansion increased employment by 7.2 percentage points, or approximately 60 percent of total employment growth, over the 1984 to 1996 period. These results imply an elasticity of LFP to net income of approximately 0.70 (Hotz and Scholz, 2003).

The most recent work, Hotz et al., (2006), uses California administrative data on families trying to make the transition from welfare to work, which includes their tax returns, to estimate the labor supply effect of the EITC. Using a difference-in-difference model they exploit the differential expansions of the EITC program over the 1990s for families with one child, two children, or three or more children. The authors find that the expansion significantly increased the employment of those who benefited. Specifically, for a family with two children, they find an elasticity of LFP to net income of 1.3, and that the expansion of the EITC increased employment by 3.2 percentage points.

Following Schulz (1996), the MaCurdy et al. (1990), Triest (1990), and Hausman (1981) substitution and income elasticities are used to simulate low, medium, and high estimates of the effect of an expansion of the New York State EITC supplement on work, income, and poverty for those currently in the labor force. For those not currently in the labor force, the elasticities of labor force participation to net income estimated in Meyer and Rosenbaum (2001), Keane and Moffitt (1998), and Eissa and Liebman (1996) are used to simulate low, medium, and high estimates of the effect of an expansion of the New York State EITC supplement on work, income, and poverty.

This paper extends the existing literature by building on the methods employed by Scholz (1996) to simulate the expansion of a state EITC supplement, and examine the effect on labor supply, income, poverty, and program expenditures. Moreover, this paper generates estimates of the impact of an EITC expansion on income, poverty and program expenditure excluding behavioral effects, which allows for a direct comparison of estimates including and excluding behavioral effects. The major contribution of this paper is its focus on the more policy relevant aspects of an EITC expansion; mainly its impact on those not in the labor force, poverty rates, and state EITC program expenditures. It also emphasizes the importance to policy makers of including behavioral estimates in models of the impact of the EITC.

2.4. Data

This simulation uses data from the Current Population Survey (CPS) Annual Social and Economic Supplement (ASEC) March 2005 (2004 income year) to simulate the effect of an expansion of the New York State EITC supplement on employment, hours worked, income, and poverty for New York State residents. The CPS is a monthly survey of approximately 60,000 households, of which approximately 1,100 are from New York State. The CPS is a nationally representative sample of the civilian non-institutionalized population. It is administered to newly recruited households for 4 consecutive months; they then go un-interviewed for 8 months, after which they are interviewed for an additional 4 consecutive months. The CPS ASEC is a supplement to the monthly CPS, which is conducted in March of each year. The ASEC surveys approximately 100,000 households, or 200,000 persons, and provides in-depth information on employment, income, non-cash benefit receipt, and migration.

Given that the data are for tax year 2004, the EITC parameters for tax year 2004 are used in the simulation. Eligibility for the EITC, as well as the value of the Federal credit, is determined by the Census Bureau using a tax simulation. To determine eligibility, the Census Bureau runs each tax unit through a tax simulation to estimate their Federal tax liabilities and the value of any tax credits. The Federal value of the EITC is included in the CPS as a family-level variable. The Census Bureau tax simulation assumes a 100 percent take-up rate for the EITC. That is, those deemed eligible for the credit by the tax simulation are assumed to receive the EITC and those not eligible are assumed not to apply. The state supplemental estimates are based on the value of the Federal EITC such families receive.

2.5. Empirical Methods

This section begins with a theoretical discussion of how the EITC program affects labor supply. It then describes the alternative definition of family income used in the calculation of poverty status. It then proceed to outline in detail the methods used to simulate the effect of an expansion of the New York State EITC supplement on employment, hours worked, income, and poverty status. Discussion is done separately for those not currently in the labor force and those in the labor force, respectively, based on the theoretical model. The simulation starts from the current 30 percent New York State Supplement to the Federal EITC and increases the value of the supplement in increments of 5 percentage points to 35 percent, 40 percent, and 45 percent of the Federal EITC benefit. At each supplement level the change in employment, hours worked, income, and poverty status relative to the current numbers are reported for those currently in the labor force and those not in the labor force separately.

2.5.1 Theoretical Predictions

Labor supply models based on microeconomic theory assume that workers have a fixed amount of time which they divide between work and leisure. Potential workers have a reservation wage (level of compensation) below which they will not work at all. Once an offer wage exceeds their reservation wage they will work, but the number of hours worked depends on the wage rate offered. Hence, the theoretical effect of the EITC on the decision to work for unmarried individuals is unambiguously positive.

Because the EITC unambiguously raises the offer wage it can only increase the likelihood that an eligible person will work. However, the availability of the EITC to married people results in less obvious overall employment outcomes. While those taking advantage of the EITC may enter the workforce, the increased income to the family could reduce the employment of other family members. Because leisure is a normal good (more of it is demanded as income increases), this increased income could lead to another earner in the family reducing overall hours worked and possibly leaving the labor force (Ellwood, 2001). Following Scholz (1996), it is assumed that all labor supply decisions are made holding constant the other spouse's earnings and that all persons who enter the labor force in response to the EITC expansion find employment, in order to simplify the analysis.[10] In other words, in this paper labor force is equated with working status and the corresponding labels are interchangeably used. This assumption appears reasonable given that it is unlikely that a single mother would enter the labor force, and potentially give up her non-labor market sources of income, unless they were able to obtain employment.

The effect of the EITC on hours worked for those already in the labor force is more ambiguous. Microeconomic theory argues that if the EITC changes the value of an additional hour of work, it will also change the income associated with that additional hour of work. The change in the value of an additional hour of work is referred to as the "substitution" effect and it implies that if workers receive a higher return from an additional hour of work they will choose to work more and reduce their leisure time, all else equal. However, a change in the income associated with that additional hour of work is referred to as the "income effect" and, because leisure is a

[10] Though Eissa and Hoynes (2005) find evidence that increases in the EITC result in modest reductions in the employment and hours worked of married women, these effects are so small that they are unlikely to affect the results of this simulation.

normal good, an increase in compensation will result in workers working less and taking more leisure.

The EITC program has three distinct regions—the phase-in, plateau, and phase-out—with the substitution and income effects operating differently in each region, resulting in a different impact on hours worked. Figure 2.1 presents the value of the Federal EITC relative to family income for single individuals, individuals with one eligible child, and individuals with two or more eligible children. For those in the phase-in region of the credit, segment A to B, the effect of the EITC is ambiguous. The rise in compensation will increase work because of the substitution effect but decrease work because of the income effect. Hence the net effect of the rise in net compensation due to the EITC in this region is uncertain.

For those in the region between the maximum eligible earnings and the beginning of the phase-out range, segment B to C, the EITC will lead to a decrease in hours worked. The value of an additional hour of work is the same as it is in the absence of the EITC so there is no substitution effect. But, because the EITC provides those in this region with greater income than they would have in the absence of the EITC, hours worked will decline due to the income effect.

For those in the phase-out region of the credit, segment C to D, the EITC will decrease hours worked. The phase-out rate of the EITC means that the value of an additional hour of work is lower than it is in the absence of the EITC because one must “pay back” part of the EITC, leading to a substitution effect that reduces hours of work. In addition, those in this region still have more income for a given amount of work than they would in the absence of the EITC and, thus, the income effect will reduce hours worked.

Figure 2.6 presents the initial budget constraint (A) faced by a single mother with two children whose hourly wage rate is $10.00 per hour and must decide how many hours to work. Imposed on this initial budget constraint is a second budget constraint (B) that includes the current Federal EITC. As can be seen, in the phase-in region (B) has a higher slope than (A). This reflects the added compensation to work from the EITC. In the plateau region, (B) is parallel to (A). While there is no longer additional compensation for work in this region, the single mother is allowed to keep all the EITC benefits already gained. In the phase-out region budget constraint (B) has a lower slope than budget constraint (A). This reflects the loss of EITC benefits previously gained and hence the lower than $10.00 net return to work. Budget constraint (C) reflects the effect of the current 30 percent New York State supplement to the Federal EITC. Because this supplement is a fixed percentage of the Federal EITC, it will increase (decrease) the slope in the phase-in (phase-out) region but not change the point with respect to hours worked at which total EITC benefits are maximized or where the plateau ends or the location of the breakeven point. The net effect of the EITC in these three regions will continue to be ambiguous in the first and negative in the second and third for those who are initially in these regions. This will also be true of any increases in the New York State supplement as can be seen in budget constraint (D) which reflects an increase in the supplement to 45 percent.

Figure 2.1 shows how Federal EITC benefits change at different labor earnings levels for three types of families. In Figure 2.3 this same kind of relationship is shown for the single mother discussed in Figure 2.2 but shows how the benefit relationship changes when the 30 percent and then 45 percent New York State supplement to her Federal EITC benefits are added.

Figures 2.2 and 2.3 illustrate that the addition of the State supplement increases the rate of ascent and descent of the credit relative to the Federal EITC alone, which potentially alters the net impact on hours worked of the substitution and income effects in each region, as additional work is now more lucrative in the phase-in region, and more punitive in the phase-out region.

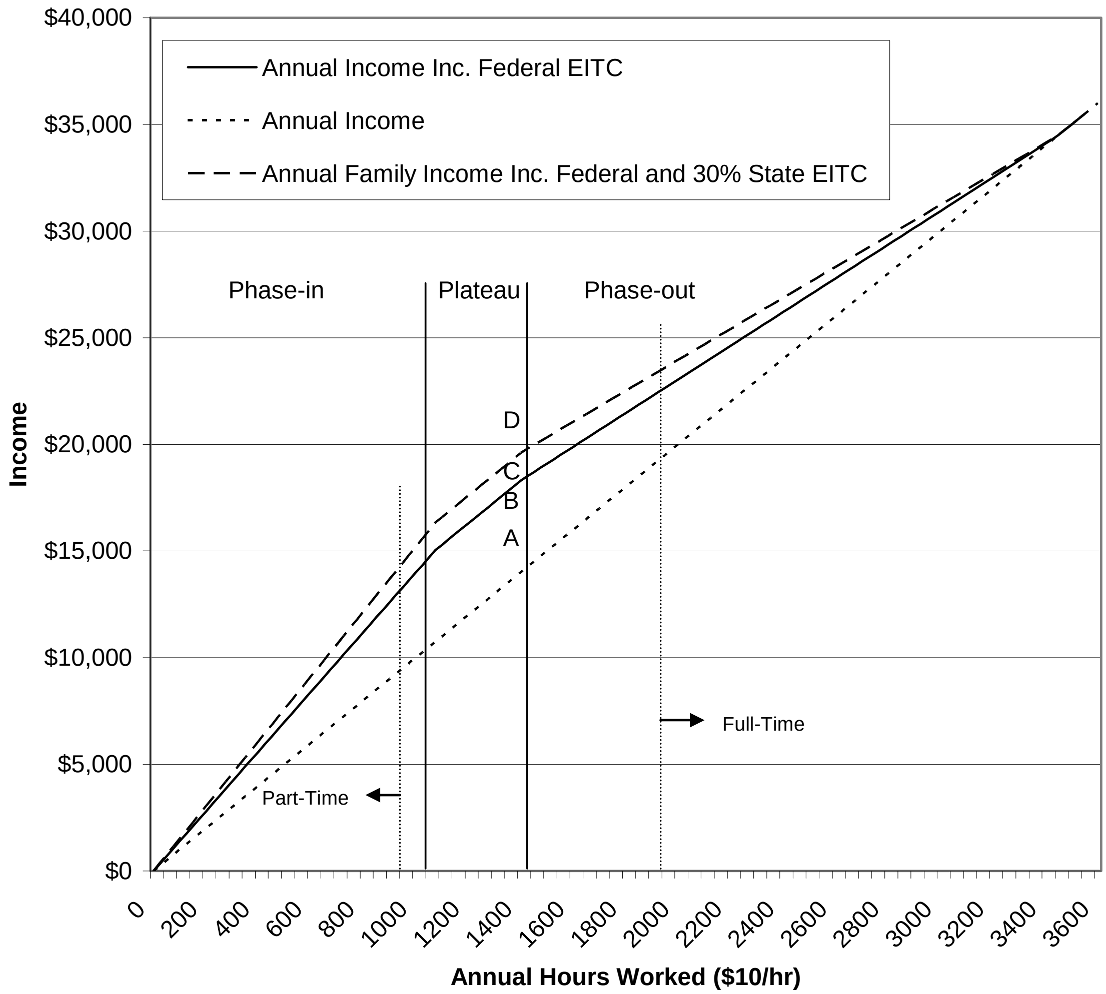

Figure 2.6. Budget Constraint for a Single Taxpayer with Two or More Children in 2004. Source: Author's Calculations

2.5.2. Alternative Definitions of Family Income

One component of the simulation is estimating changes in poverty resulting from changes in the generosity of New York State's EITC supplement program. The standard definition of poverty adds up labor earnings and cash welfare payments and compares this to a family-size adjusted poverty line. However, given that this analysis focuses on the EITC, it would be inappropriate to use a definition of income for determining poverty which excluded the substantial contribution of the EITC to the incomes of low-income families. The Census Bureau has developed several alternative income measures, which are used to examine the change in the official poverty rate that would result from the inclusion of income from programs, such as the EITC, in the income-to-needs calculation.[11] Here an expanded definition of income is used based on the Census Bureau alternative income measure called MI-Tx+NC to determine poverty status, as this measure captures the substantial contribution of programs such as the EITC to the incomes of low-income families.[12] The Census Bureau MI-Tx+NC measure adds the value of in-kind transfers (food stamps, school lunch, housing subsidies, and home energy subsidies), as well as the Federal EITC to family income, but subtracts state, Federal, and FICA tax payments from family income. The income measure used in this paper further includes the value of State EITC benefits. In order to determine whether persons in a family are poor a family's expanded alternative income value is compared to their corresponding poverty line, and if below the poverty line, the individuals in that family are defined as poor. This paper only applies this alternative definition of poverty.

2.5.3. Simulation Methods for those Persons Not in the Labor Force at the Time of the Expansion

Because, by definition, the data contains far less information on the labor force characteristics of those not in the labor force, a significant number of assumptions are required in order to simulate the effect of a state EITC supplement expansion on the

[11] See Dalaker 2005 for a more detailed description of the alternative poverty measures.
[12] MI-Tx+NC refers to money income minus taxes plus non-cash benefits. It is possible that Tx is negative since the EITC is a refundable tax credit and hence can lead to some person's receiving "tax benefits" from the government rather than paying taxes to the government. In this case Tx is added to and not subtracted from money income.

employment, number of hours worked, income, and poverty status of those not in the labor force. Specifically, we do not observe the wage that these individuals would receive should they choose to enter the labor force, nor do we observe the annual number of hours they would choose to work. Thus three key assumptions are made regarding the characteristics single mothers would have should they enter the labor market. The first assumption is that all those not in the labor force who choose to enter the labor force as a result of the EITC expansion would earn the current New York State minimum wage of $7.15. The one previous study to simulate the change in income for those who enter the labor force—Scholz (1996)—uses predicted wages. However, this study makes a more conservative assumption of the earnings of labor market entrants, and assumes they earn the NY State minimum wage. The second assumption is that labor market entrants would work the same number of hours as the average person of similar characteristics who is currently in the labor force. For example, the average single mother works 1633 hours per year in the 2005 CPS ASEC and so single mothers outside the labor force are assumed to work 1633 hours per year should they choose to enter the labor force. Lastly, given the complexity of calculating benefit receipt from the numerous income support programs available to low-income working families—and included in the alternative measure of family income—it is simply assumed that all persons who choose to join the labor force as a result of an EITC expansion had been poor and become non-poor.[13]

[13] Though the assumption that all persons who join the labor force as a result of an EITC expansion become non-poor may seem rather strong, it is actually quite reasonable given that just by counting wages, current combined New York State and Federal EITC benefits, the refundable portion of the Federal Child Tax Credit and subtracting FICA taxes for a single mother with two or more children who works 1,633 hours per year at the minimum wage of $7.15 family income would be $15,733—just beyond the poverty line of $15,670 for a family of three. Moreover, the inclusion of the value of in-kind benefits such as housing subsidies, food stamps, home energy subsidies, and school lunches—as is done when calculating alternative family income—would push the family even further above the poverty line. On average, a family with two or more children earning approximately $11,500 in wages received about $800 worth of in-kind benefits. Even if the assumption that a new labor force entrant would work 1,633 hours per year is viewed as high, one should point out that even working half-time (20 hours per week, 52 weeks per year) a single mother with two children would only need a wage rate of $10 per

Given the assumptions cited above, the primary simulation method for the effect of an EITC expansion on those not in the labor force at the time of the expansion of EITC involves determining the number of these persons who would enter the labor force for a given change in the EITC supplement. This is done using elasticities of labor force participation to net income drawn from the existing literature on the effect of the EITC on labor supply. An elasticity of labor force participation to net income gives the percent change in labor force participation for a given percent change in net income—where net income is defined as income after State and Federal taxes, including EITC benefits, and FICA taxes. The percent change in net income for those not in the labor force is calculated by taking the current net income a person would receive were they participating in the labor force at the assumed wage and number of hours, and then calculating the additional income they would receive from each expansion of the New York State EITC supplement. For example, a single mother with one child earning $11,676 in labor income would receive $1,845 back from the Federal and State governments after adding in state and federal EITC benefits and subtracting out FICA taxes yielding a net income of $13,521. An expansion of the New York State EITC Supplement to 35 percent of the federal benefit would add $130 to her net income (0.96%), an expansion to 40 percent would add $261 to her net income (1.93%), and an expansion to 45 percent would add $391 to her net income (2.89%). A single mother with two children earning $11,676 in labor income would receive $4,057 back from the Federal and State governments after adding in state and federal EITC benefits and subtracting out FICA taxes yielding a net income of $15,733. An expansion of the New York State EITC Supplement to 35 percent of the federal benefit would add $215 to her net income (1.37%), an expansion to 40 percent

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hour to exceed the poverty line once all transfers and in-kind benefits were included in family income. In addition, single mothers who do not work have poverty rates above 80% and it is reasonable to assume all those who join the labor force are poor. (Source: All figures were calculated by the author using the CPS ASEC 2005.)

would add $430 to her net income (2.73%), and an expansion to 45 percent would add $645 to her net income (4.10%).

Separate elasticity estimates exist for men, married women, and single mothers as their labor supply decisions are fundamentally different. Back of the envelope calculations using an elasticity of labor force participation to income of 0.03 for men and 0.26 for married women from Eissa and Hoynes (2004) and the EITC program parameters indicated that an EITC supplement expansion would only induce labor force entry by single mothers. Men are excluded as a result of their very low elasticity, implying minimal changes in participation even for large changes in the EITC benefit. Married women are excluded because a married woman entering the labor force faces a very high marginal tax rate, as the EITC program only extended the phase-in and plateau regions by $1,000 for a married couple in 2004, which make changes in net family income small or even zero. Lastly, though single childless persons can be eligible for the EITC, they can only earn a maximum state and federal benefit of $507, which is completely phased out if they earn more than $11,490. These EITC parameters for the childless yield very small changes in net income for any reasonable number of annual hours worked. With the exclusion of these three groups, the simulation for those not in the labor force is only conducted for single mothers.

In order to provide low, medium, and high estimates of the effect of an EITC supplement expansion on the employment of single mothers, three different elasticities of labor force participation to net income are employed in the simulation. The three elasticities are: 0.69 from Meyer and Rosenbaum (2001) for a lower bound; 0.96 from Keane and Moffitt (1998) for the medium; and 1.16 from Eissa and Liebman (1996) for an upper bound. These elasticities were selected as they covered the range of estimates found in the existing EITC literature. These elasticities imply that for a 10 percent increase in net income, labor force participation of single mothers will increase by 6.9 percent, 9.6 percent, and 11.6 percent, respectively. These and other elasticities of labor force participation to net income are presented in Table 2.2 in order to give the reader a sense for the range of estimates produced by the EITC literature.

The next step involved producing the labor force participation rates for single mothers. Given that mothers with one child and mothers with two or more children participate in the labor force at different rates, labor force participation rates were estimated separately. Estimates from the 2005 CPS ASEC indicate that there were 394,915 single mothers with one child in New York State and their labor force participation rate was 79.47 percent, and that there 321,611 single mothers with two or more children and their labor force participation rate was 70.88 percent. With labor force participation rates for these two groups, the simulated changes in employment among those not in the labor force were obtained by applying the above mentioned percent changes in net income for a given change in the EITC supplement with the three elasticities of labor force participation to net income to the respective labor force participation rates yielding percentage point changes in the labor force participation rate. These percentage point changes were then converted into actual numbers of persons by applying them to the respective total populations of single mothers. For example, a one percentage point increase in the labor force participation rate of single mothers with one child would increase the number in the labor force by 3,949 mothers and affect 7,898 persons (1 mother and 1 child in each family). For single mothers with two or more children, one percentage point increase in their labor force participation rate would increase the number in the labor force by 3,216 mothers and affect 11,256 persons (1 mother and an average 2.5 children in each family). All these persons are then assumed to have been poor and exit poverty based on the above mentioned assumptions.

The change in employment, hours worked, and earnings for those persons not in the labor force at the time of the expansion of the EITC are presented in the "Not in Labor Force" columns of Table 2.3, while the average values are presented in Table 2.4. Detailed poverty numbers are presented in Table 2.5. The poverty numbers are separated into those not in the labor force and those in the labor force given that the estimates for those not in the labor force at the time of the EITC expansion are likely to be less precise than for those who are employed at the time of the EITC expansion.

2.5.4. Simulation Methods for those Persons in the Labor Force at the Time of the Expansion

The simulations of the effect of increases in the New York State EITC Supplement for those not in the labor force presented here are based on those first developed in Scholz (1996). The procedure begins by determining who is currently eligible for the EITC and their EITC region—phase-in, plateau, or phase-out. EITC eligibility is determined using the Census Bureau-derived variable eit_cred, the estimated value of the family's Federal EITC, in the CPS data. If the eit_cred value is positive a person is eligible for the EITC. Their region is then assigned based on their own wages, or their wages plus their spouse's wages where appropriate, and their number of children. As discussed in the theoretical background on the EITC's labor supply effects, it is necessary to know the person's EITC region to determine the substitution effect since the new marginal tax rate an individual faces, which is relevant for the calculation of the substitution effect, depends on the person's EITC region.

For those in the labor force, the most important aspect of the simulation is determining the change in hours worked per year for a given change in the EITC supplement. The change in hours worked is the net of the substitution and income effects resulting from changes in income. As calculating the change in hours worked is significantly different for the substitution and income effects, they are calculated separately, and then combined at a later stage.

As with the simulation for those not in the labor force, low, medium, and high estimates of the changes in hours worked, income, and poverty in response to a change in the EITC supplement are provided by using three sets of uncompensated wage and income elasticities drawn from the previous literature. Specifically, estimates of the uncompensated wage elasticity and income elasticity are obtained from MaCurdy et al. (1990), Triest (1990), and Hausman (1981) for both women and men as lower-bound, medium, and upper-bound estimates, respectively, as done in Dickert et al. (1995) and Schulz (1996). These elasticities are presented in the last six columns of Table 2.2.

For the substitution effect, the change in hours worked is calculated by applying the uncompensated wage elasticity to the percent change in the marginal tax rate an individual faces as a result of a change in the New York State EITC supplement (i.e. the numerator is the change in the EITC and the denominator includes all taxes, not simply the EITC.)[14] An individual's marginal tax rate is calculated as the 15.3 percent FICA rate, minus their federal EITC rate plus their federal tax rate minus their state EITC rate plus their state tax rate. Though the New York State EITC benefit is a set rate of the federal benefit, this implicitly alters the rate at which the credit is accumulated in the phase-in region and withdrawn in the phase-out region.

[14] Many families who receive the EITC also receive in-kind benefits, such as food stamps, which are phased-out as income increases. Hence changes in the EITC program that increased countable income in these programs, reducing their value would affect the implicit marginal tax rate faced by a worker. However, the EITC benefit itself is not counted in the calculation of in-kind benefits. But any labor earnings increase caused by a change in the EITC benefit rules would be affected because labor earnings are countable income in such programs. The denominator used to calculate the percent change in the marginal tax rate here does not include the implicit tax rates on labor earnings from lost benefits from these in-kind programs. The microsimulation required to capture those rates is beyond the scope of this paper. However, given the relatively small change in labor earnings the simulation produces, the addition of these implicit taxes is unlikely to substantially affect the results presented here.

Table 2.2. Labor supply parameters for EITC simulation

	Elasticity of Labor Force Participation to Net Income			Uncompensated Wage Elasticity			Income Elasticity		
	Men	Married Women	Single Women	Men	Married Women	Single Women	Men	Married Women	Single Women
Elasticities for those working:									
Low: MaCurdy et al (1990)				0	0.11	0.11	0	-0.01	-0.01
Medium: Triest (1990)				0.06	0.27	0.27	0	-0.16	-0.16
High: Hausman (1981)				0.02	0.78	0.78	-0.17	-0.1	-0.1
Elasticities for those not working:									
Low: Meyer and Rosenbaum (2001)			0.69						
Medium: Keane and Moffitt (1998)			0.96						
High: Eissa and Liebman (1996)			1.16						
Other elasticities from the literature:									
Dickert, Houser, and Scholz (1995)			0.85						
Eissa and Hoynes (1998)	0.03	0.29		0.06-0.07	0.08-0.52		0.0	-0.04 to -0.41	
Hotz, Mullin, and Scholz (2002)			0.97-1.69						
Keane and Moffitt (1991)						0.66			-0.24

Table 2.3. Changes in Employment, Hours Worked, Earnings, and State EITC Cost

State Supplement as a Percent of the Federal EITC	Change in Number Employed Ages 18-64			Change in Hours Worked (in 1000s)			Change in Labor Earnings (in $1000s)			Change in State EITC Benefits (in $1000s)		
	(1) Working	(2) Not Working	(3) Total	(4) Working	(5) Not Working	(6) Total	(7) Working	(8) Not Working	(9) Total	(10) Working	(11) Not Working	(12) Total
Low Estimate:†												
35%	----	4,238	4,238	-121	6,921	6,799	-5,994	49,482	43,488	79,644	5,138	84,783
40%	----	5,896	5,896	-347	9,629	9,281	-12,912	68,845	55,933	159,477	7,149	166,626
45%	----	7,125	7,125	-563	11,635	11,071	-19,775	83,187	63,413	238,900	8,638	247,538
Medium Estimate:‡												
35%	----	8,473	8,473	-1,201	13,836	12,635	-18,368	98,927	80,559	80,864	11,742	92,605
40%	----	11,788	11,788	-2,425	19,250	16,825	-37,710	137,637	99,928	162,267	16,336	178,603
45%	----	14,244	14,244	-3,867	23,260	19,393	-70,497	166,312	95,815	245,392	19,740	265,131
High Estimate:*												
35%	----	12,707	12,707	-1,460	20,751	19,291	-47,205	148,372	101,167	86,799	19,812	106,611
40%	----	17,680	17,680	-3,742	28,871	25,129	-101,393	206,430	105,037	174,929	27,565	202,493
45%	----	21,363	21,363	-5,951	34,886	28,935	-155,180	249,436	94,256	260,294	33,307	293,601

Source: Author's Calculations using Current Population Survey Annual Social and Economic Supplement (ASEC), 2005.
Note: The estimated values at the current 30 percent NY State EITC Supplement are: 10.0 million persons employed; 1.5 billion hours worked; $11.8 billion in labor earnings; and 471.0 million in NY State EITC benefits paid.
† : The low estimates are simulated using the MaCurdy et al. (1990) elasticities for those initially working and the Meyer and Rosenbaum (2001) elasticities for those not initially working.
‡ : The medium estimates are simulated using the Triest (1990) elasticities for those initially working and the Keane and Moffitt (1998) elasticities for those not initially working.
* : The high estimates are simulated using the Hausman (1981) elasticities for those initially working and the Eissa and Liebman (1996) elasticities for those not initially working.

Table 2.4. Simulated Changes in Average Hours Worked, Average Earnings, Average EITC Benefits, and Average Alternative Family Income for Various Increases in the NY State EITC Supplement

		Working			Not Working		
		State Supplement as a Percent of the Federal EITC(a)			State Supplement as a Percent of the Federal EITC(b)		
		(1) 35%	(2) 40%	(3) 45%	(4) 35%	(5) 40%	(6) 45%
Average Change in Hours Worked Per Year Per Person	Low Estimate†	-0.11	-0.33	-0.53	1633.00	1633.00	1633.00
	Medium Estimate‡	-1.14	-2.30	-3.67	1633.00	1633.00	1633.00
	High Estimate*	-1.38	-3.55	-5.64	1633.00	1633.00	1633.00
Average Change in Annual Labor Earnings	Low Estimate†	-$6	-$12	-$19	$11,676	$11,676	$11,676
	Medium Estimate‡	-$17	-$36	-$67	$11,676	$11,676	$11,676
	High Estimate*	-$45	-$96	-$147	$11,676	$11,676	$11,676

Source: Author's Calculations using Current Population Survey Annual Social and Economic Supplement (ASEC), 2005.
Notes:
(a) For those initially working the average values at the current 30 percent NY State EITC Supplement are: 1467 hours worked; $11,214 in labor earnings; $1,936 in EITC benefits; and Alternative Family Income of $27,399.
(b) For those not initially working the assumed values at the current 30 percent NY State EITC Supplement are: 0 hours worked; $0 in labor earnings; $0 in EITC benefits; and Alternative Family Income of $8,599 (calculated from CPS).
† : The low estimates are simulated using the MaCurdy et al. (1990) elasticities for those initially working and the Meyer and Rosenbaum (2001) elasticities for those not initially working.
‡ : The medium estimates are simulated using the Triest (1990) elasticities for those initially working and the Keane and Moffitt (1998) elasticities for those not initially working.
* : The high estimates are simulated using the Hausman (1981) elasticities for those initially working and the Eissa and Liebman (1996) elasticities for those not initially working.

Table 2.4. (Continued)

		Working			Not Working		
		State Supplement as a Percent of the Federal EITC(a)			State Supplement as a Percent of the Federal EITC(b)		
		(1) 35%	(2) 40%	(3) 45%	(4) 35%	(5) 40%	(6) 45%
Average Change in Federal and State EITC Benefits	Low Estimate†	$80	$160	$240	$4,688	$4,862	$5,035
	Medium Estimate‡	$86	$173	$272	$4,688	$4,862	$5,035
	High Estimate*	$116	$230	$347	$4,688	$4,862	$5,035
Average Change in Alternative Family Income	Low Estimate†	$77	$152	$228	$7,765	$7,939	$8,112
	Medium Estimate‡	$73	$144	$215	$7,765	$7,939	$8,112
	High Estimate*	$75	$144	$214	$7,765	$7,939	$8,112

Table 2.5. Various Estimates of Reductions in Alternative Poverty Rates of All New York Residents as a Result of Expansion of State EITC

	Estimated Changes in Alternative Total Poverty-No Behavioral Effects			Estimated Change in the Alternative Poverty with Behavioral Effects: Low Estimates†			Estimated Change in the Alternative Poverty with Behavioral Effects: Medium Estimates‡			Estimated Change in the Alternative Poverty with Behavioral Effects: High Estimates*			Medium Estimates of Changes in the Alternative Child Poverty		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
State Supplement as a Percent of the Federal EITC(a)	Change in Poverty Count (in 1000s)	Poverty Rate	Change in Poverty Rate	Change in Poverty Count (in 1000s)	Poverty Rate	Change in Poverty Rates	Change in Poverty Count (in 1000s)	Poverty Rate	Change in Poverty Rates	Change in Poverty Count (in 1000s)	Poverty Rate	Change in Poverty Rates	Change in Poverty Count (in 1000s)	Poverty Rate	Change in Poverty Rates
Working:															
35%	-3			-3			-6			-16			-1		
40%	-12			-15			-35			-30			-8		
45%	-30			-33			-38			-39			-17		
Not Working:															
35%	----		----	-12			-16			-20			-10		
40%	----		----	-23			-33			-39			-21		
45%	----		----	-35			-49			-59			-31		
Total:															
35%	-3	11.75%	0.00	-15	11.67%	-0.08	-22	11.63%	-0.12	-35	11.56%	-0.19	-12	14.82%	-0.25
40%	-12	11.65%	-0.10	-38	11.55%	-0.20	-67	11.39%	-0.35	-69	11.39%	-0.36	-29	14.43%	-0.64
45%	-30	11.55%	-0.20	-68	11.39%	-0.36	-86	11.29%	-0.45	-98	11.23%	-0.52	-48	14.01%	-1.06

Source: Author's Calculations using Current Population Survey Annual Social and Economic Supplement (ASEC), 2005.
Notes:
(a) Alternative poverty count for all persons in NY State in 2004 was 2,233,000 and the poverty rate was 11.75%. The poverty count for all children in NY State in 2004 was 686,000 implying a child poverty rate of 15.07%.
† : The low estimates are simulated using the MaCurdy et al. (1990) elasticities for those initially working and the Meyer and Rosenbaum (2001) elasticities for those not initially working.
‡ : The medium estimates are simulated using the Triest (1990) elasticities for those initially working and the Keane and Moffitt (1998) elasticities for those not initially working.
* : The high estimates are simulated using the Hausman (1981) elasticities for those initially working and the Eissa and Liebman (1996) elasticities for those not initially working.

Table 2.6. Comparison of Effects of EITC Expansion from 30 to 45 percent with and without Behavioral Responses

		(1) Behavioral Effects (Medium Estimates)‡	(2) No Behavioral Effects	(3) Difference
Employment				
	Working	0	0	0
	Not Working	14,244	0	14,244
	Total	14,244	0	14,244
Hours Worked (In 1000s)				
	Working	-3,867	0	-3,867
	Not Working	23,260	0	23,260
	Total	19,393	0	19,393
Labor Earnings (In 1000s)				
	Working	-70,497	0	-70,497
	Not Working	166,312	0	166,312
	Total	95,815	0	95,815
State EITC Benefits (In 1000s)				
	Working	245,392	235,513	9,879
	Not Working	19,787	0	19,787
	Total	265,179	235,513	29,666
Family Income (In 1000s)				
	Working	226,276	235,513	-9,237
	Not Working	93,757	0	93,757
	Total	320,033	235,513	84,520
Persons in Poverty				
	Working	-37,535	-29,776	-7,759
	Not Working	-48,817	0	-48,817
	Total	-86,352	-29,776	-56,576

Source: Author's Calculations using Current Population Survey Annual Social and Economic Supplement (ASEC), 2005.
‡ : The medium estimates are simulated using the Triest (1990) elasticities for those initially working and the Keane and Moffitt (1998) elasticities for those not initially working.

For example, a tax unit with two or more eligible children faces an implicit additional credit rate of 12.0 percent in the phase-in region, and an additional phase-out rate of 6.32 percent in the phase-out region.[15] An increase in the New York State EITC supplement rate to 35 percent would change the credit rates to 14.00 percent in the phase-in region and 7.37 in the phase-out region. The credit or phase-out rate of the EITC forms part of the marginal tax rate an individual faces in making their labor supply decision as it alters their after tax wage rate. An increase in the EITC credit rate of 1 percent increases an individual's after-tax wage by 1 percent. Similarly, an increase in the phase-out rate of 1 percent decreases an individual's after-tax wage by 1 percent. Thus, the substitution effect positively affects hours worked in the phase-in region as an increase in the EITC decreases the effective marginal tax rate an individual faces. In the plateau region the substitution effect does not operate, as changes in the EITC credit or phase-out rate do not affect an individual's effective marginal tax rate since their EITC benefit is neither increasing nor decreasing with changes in income. In the phase-out region the substitution effect negatively affects hours worked as an increase in the EITC's phase-out rate increases the effective marginal tax rate an individual faces making an additional hour of work less lucrative.

The marginal tax rate of a tax unit with two or more children in the phase-in region is the federal income tax rate plus the state income tax rate—if any earnings are subject to tax after deductions and exemptions—plus the FICA tax rate, minus the federal EITC credit rate, minus the effective New York State EITC credit rate. In this region most families' deductions and exemptions will make it unlikely that they will be subject to federal or state income taxes, so their marginal tax rate will be: -36.7 percent (15.3 percent FICA – 40 percent federal EITC + 0 percent federal tax rate – 12 percent state EITC + 0 percent state tax rate). That is, with each additional dollar

[15] The implicit New York State rates are calculated by multiplying the federal rates by 30 percent.

earned their net tax liability decreases by 36.7 cents. Given that the EITC is refundable, this is equivalent to each dollar in wages actually being worth $1.367 after taxes. Thus, increasing the New York State supplement to 35 percent of the federal credit would reduce the marginal tax rate of a tax-unit with two or more children in the phase-in region by an additional two percentage points as the state EITC credit rate would increase from 12 percent to 14 percent. With an initial marginal tax rate of -36.7 percent, the percent change in marginal taxes equals -5.45 percent (2/-36.7). Taking the low uncompensated wage elasticity for women of 0.11 from MaCurdy et al. (1990), this 5.45 percent decrease in the marginal tax rate would result in an increase in hours worked of 0.6 percent (5.45*0.11).

In the phase-out region this effect operates in reverse to reduce hours worked. A tax unit with two or more eligible children earning $25,000 per year faces a marginal tax rate of 57.18 percent (15.3 percent FICA + 21.06 percent federal EITC + 10 percent federal tax rate + 6.32 percent state EITC + 4.5 percent state tax rate). Increasing the New York State EITC supplement rate to 35 percent results in her marginal tax rate increasing by 1.05 percentage points (1.84%), as her state marginal tax rate would increase to 11.87 percent. Again using the low uncompensated wage elasticity for women of 0.11 from MaCurdy et al. (1990), this 1.84 percent increase in her marginal tax rate would result in a decrease in hours worked of 0.20 percent (1.84*0.11).

Since everyone in a given EITC eligibility category—childless, one child, two or more children—and region of the EITC faces the same percentage point change in their marginal tax rate with an expansion of the EITC supplement, changes in marginal tax rates are calculated and then assign by eligibility category and credit region for an expansion to a 35, 40, and then 45 percent supplement. As the marginal tax rate for each tax unit is provided in the CPS, calculating the percent change in the marginal tax rate faced by a person after each simulated expansion of the EITC supplement involves simply dividing the assigned percentage point change in the marginal tax rate by the CPS assigned current marginal tax rate. With the percent change in marginal tax rate calculated, each of the three uncompensated wage elasticities are then applied for each of the three expansions of the credit, which yields low, medium, and high estimates of the change in hours worked due to the substitution effect at a supplement rate of 35 percent, 40 percent, and 45 percent.

For the income effect, determining the change in hours worked is similar to the process used to determine the change in employment for those not in the labor force. As with those not in the labor force, calculations are made on the basis of net income, which is defined as income after State and Federal taxes, including EITC benefits, and FICA taxes. However, for those in the labor force it is possible to calculate actual net income based on income and taxes reported in the CPS. In order to apply the income elasticities a person's percent change in net income is calculated by determining the change in the value of the New York State EITC supplement for a given increase in the supplement rate at their current CPS determined income level and dividing this change in their supplement by their net income. The variable eit_cred is used as the basis for the estimate of the value of the New York State EITC supplement. Beginning in the March 2004 CPS, the Census Bureau included the value of the state EITC supplement in the variable for total state taxes. However, given that the state tax is a net value, the amount of the state EITC is not directly available.[16] Therefore, estimates of a tax unit's New York state EITC value are obtained by multiplying the value of the Federal credit provided in the CPS by 0.30. The value of a change in the New York State EITC supplement to 35 percent, 40 percent, and 45 percent of the federal credit

[16] Unless the value of the state EITC supplement exceeds a person's total tax liabilities, the net state tax variable will show a positive amount of taxes owed. The value of the state EITC supplement is not provided as a separate variable. Therefore it is necessary to impute the value of the state EITC supplement from the value of the Federal EITC, which is reported.

was then calculated by multiplying each family's eit_cred value by 0.05, 0.10, and 0.15 respectively.

In order to determine the percent change in hours worked due to the income effect, the percent change in net income that we determined for each person at each of the three expansions of the EITC supplement is taken and applied to the gender appropriate low, medium, and high income elasticities. With both the income and substitution effects now estimated for all three simulated EITC supplement expansions using the low, medium, and high elasticities, the effects on hours worked are added together to determine the net percent change in hours worked by each person. This is then converted into actual hours by multiplying the percent change in hours worked by the number of hours worked per year.

Based on the net change in hours worked per year a person's net income is recalculated by multiplying their net of tax wage rate by the change in the number of hours they worked and adding this value to their previous net income. For example, a person who reduced their hours worked by 10 hours per year as a result of the EITC expansion, who earned $10 per hour, and faced a marginal tax rate of 50 percent would have their net income reduced by $50 ($10*0.5 tax rate*-10 hours). Given that this change in income may have resulted in a person moving into, or out of poverty, poverty status is recalculated using the new value for net income.

Due to the complexity of recalculating the value of food stamps, school lunches, housing subsidies, and home energy subsidies for a given change in earnings due to an EITC expansion, the value of these benefits is held constant, so changes in alternative family income only result from changes in net of tax wage earnings. As the results of the simulation indicate only minor changes in labor earnings for the average person, the value of these benefits is unlikely to be significantly altered were their value to be recalculated at the new income level. Moreover, the net effect on average alternative family income is ambiguous. Since EITC benefits are not counted as income in determining the amount of in-kind benefits received from these programs to the degree persons in the plateau and phase-out region reduce their labor earnings, potentially increasing the value of their in-kind benefits, this will offset the decline in potential in-kind benefits of those in the phase-in region who increase their labor earnings. In order to determine changes in poverty, the alternative income value is compared to the poverty line with each step in the simulated expansion of the New York State EITC supplement, and if below the poverty line, the individuals in that family are defined as poor.

2.6. Empirical Results

Table 2.3 presents the change in employment based on the low, medium, and high elasticities of LFP to net income, and hours worked, labor earnings, and NYS EITC benefits based on the low, medium, and high labor supply parameters, respectively. This table divides the effect between those in the labor force (initially working) and those not in the labor force (those not initially working). With regards to changes in employment, under no set of parameters would anyone currently in the labor force exit the labor force (column 1), as those who originally chose to work would not stop working as working becomes even more rewarding. However, there are a significant number of persons who enter the labor force (column 2) as a result of an EITC expansion. As discussed above, the only persons induced to enter the labor force given the assumptions of this model are single mothers. Focusing on an expansion of the NYS EITC to 45 percent of the federal credit, it is estimated that at the low end an additional 7,125 single mothers would enter the labor force, 14,244 would enter under the medium estimate, and 21,363 would enter under the high estimates (column 3).

Columns 4, 5, and 6 of Table 2.3 present the estimated change in hours worked. As expected from the previous literature and the theoretical assumptions, the number of hours worked by those currently in the labor force declines with an expansion of the NYS EITC. Estimates of the decline in hours worked with an expansion to a 45 percent NYS EITC range from 563,000 hours per year to 5.951 million hours per year for those currently in the labor force (column 4). However, the decline in hours worked by those in the labor force is more than offset across all specifications by the increase in hours worked by those not in the labor force prior to the expansion. The increase in hours worked by those not previously in the labor force is estimated to range from 11.635 million to 34.886 million (column 5). The net effect is an increase in hours worked of between 11.071 million and 28.935 million (column 6).

Columns 7, 8, and 9 of Table 2.3 present the estimated change in labor earnings. Owing to the decline in hours worked by those in the labor force, an expansion to a 45 percent NYS EITC is estimated to reduce their labor earnings by between $19.775 million and $155.180 million (column 7). Again, this is more than offset by the estimated increase in the labor earnings of those entering the labor force of between $83.187 million and $249.436 million (column 8). On net, this implies that an expansion to a 45 percent NYS EITC yields an increase in the labor earnings available to low-income families of between $63.413 million and $94.256 million (column 9).

Columns 10, 11, and 12 of Table 2.3 present the estimated change in NY State EITC benefits paid. With an increase in the EITC supplement rate, benefit payments increase to both those in the labor force and not in the labor force. For those in the labor force, the increase in EITC benefits due to the expansion of the credit rate offsets the decline in hours worked. Again taking the example of a 45 percent NYS EITC supplement, payments to those in the labor force increase by between $238.900 million with the low estimate and $260.294 million with the high estimate. For those not in the labor force increasing the NYS EITC supplement to 45 percent results in an increase in benefits of between $8.638 million and $33.307 million. This results in a net increase in NYS EITC expenditures (benefits received) of between $247.538 million and $293.601 million.

Table 2.4 presents the simulated effect of an EITC expansion on hours worked, labor earnings, combined NYS and federal EITC benefits, and alternative family income separately for the average person initially in the labor force and not initially in the labor force. With an expansion to a 45 percent NYS EITC supplement the average person in the labor force decreases their hours worked by between 0.53 and 5.6 hours per year (column 3), while the hours worked of those not initially in the labor force increases by the assumed 1633 hours (column 6). As a result, the average labor earnings of those initially in the labor force decline by between $19 and $147 (column 3), while average labor earnings of those initially in the labor force decline by the assumed $11,676 (column 6).

For those initially in the labor force, the decline in labor earnings is more than offset by increased federal and state EITC benefit payments, which range from an additional $240 to $347 (column 3). The net effect on family income is shown in the average alternative family income rows, which indicate that average family income changes by between $228 and $214 relative to its pre-EITC expansion value of $27,399.

For those not initially in the labor force, they are assumed to go from $0 in state and federal EITC benefits to the combined maximum benefit at a 45 percent state supplement rate, which averaged between women with one child and two or more children yields $5,035 (column 6). Adding the assumed annual labor earnings and the assumed EITC benefit together yields an income of $16,711. However, as most single mothers not initially in the labor force report some family income, the average value of family income for single mothers not initially in the labor force of $8,599 is subtracted from the $16,711 they are assumed to earn in the labor force in order to get a change in family income of $8,112.

Table 2.5 presents the simulated effect of an EITC expansion on poverty by combining the low, medium, and high estimated change in poverty for those initially in the labor force with the low, medium, and high estimated change in poverty for those not initially in the labor force who enter the labor force. Table 2.5 also presents the estimated change in poverty without any behavioral assumptions.

As a result of increased labor force participation and increased EITC benefit receipt, the expansion of the NYS EITC has a significant effect on the number of persons in poverty. With an expansion of the credit to 45 percent, poverty is decreased by approximately 33,000 persons (adults and children) among those in the labor force, and approximately 35,000 persons among those who enter the labor force under the low estimate (column 4). Under the medium estimates, poverty is decreased by approximately 38,000 persons among those in the labor force, and by approximately 49,000 persons among those who enter that labor force (column 7). Under the high estimates, poverty is decreased by approximately 39,000 persons among those in the labor force, and by approximately 59,000 persons among those who enter that labor force (column 10). Thus total poverty is estimated to fall by between 68,000 and 98,000 persons with a 45 percent increase in the NYS EITC supplement rate.

With an expansion of the NYS EITC credit to 45 percent, the total poverty rate declines from the current 11.75 percent to 11.39 percent under the low parameters (column 5), 11.29 percent under the medium parameters (column 8), and 11.23 percent under the high parameters (column 11). As the effect on poverty rates for those in the labor force varies little by low, medium, or high estimate, the child poverty rates are only presented for the medium estimate. With an expansion of the NYS EITC from 30 percent to 45 percent it is estimated that the child poverty rate would decline from the current 15.07 percent to 14.01 percent (column 14).

Table 2.5 also presents poverty rates using a model with no behavioral effects. The model without behavioral effects understates the reduction in poverty relative to even the low estimate using behavioral effects. Moreover, it completely misses the even greater reductions in poverty for those who enter the labor force. With an expansion of the NYS EITC from 30 percent to 45 percent, and assuming no behavioral effects, the total number of people in poverty is estimated to fall by 30,000 (column 1), or from the current poverty rate of 11.75 percent to a poverty rate of 11.55 percent (column 2), for a reduction of 0.20 percentage points (column 3). For the medium estimates of behavioral change, the number of people in poverty is reduced by 49,000 from those who enter the labor force and by 38,000 for those who were initially in the labor force for a total of 86,000 (column 7). Thus, overall poverty reduction is underestimated by approximately 56,000 when behavioral changes are not considered.

Table 2.6 presents side by side comparisons of the results using the medium parameters for behavioral effects and results omitting behavioral effects for all outcomes of interest. In terms, of employment, hours worked, and labor earnings the model with no behavioral effects estimates no change in these outcomes by definition. In contrast, the simulation results using the medium parameters for behavioral effects estimates an increase in employment of 14,244 persons, a net increase in hours worked of 19.393 million, and a net increase in labor earnings of $95.815 million.

With regards to program expenditures, Table 2.6 shows that omitting behavioral effects, an increase in the NYS EITC Supplement rate from 30 to 45 percent will result in additional program expenditures, or benefits paid, of $235.513 million. Based on the medium estimates, this is $9.879 million less than the estimated benefits paid to those in the labor market at the time of the EITC change using the behavioral model, and misses completely the $19.787 million in estimated additional benefits paid to the new labor market entrants. Thus, the model without behavioral effects understates the increased costs of expanding the EITC program by a total of $29.666 million.

In the model with no behavioral effects, the only change in family income occurs through the change in the amount of the state EITC benefit received. However, in the behavioral model labor supply, and the values of labor earnings, state taxes, and federal taxes/EITC benefit are allowed to vary in addition to the state EITC benefit. Using the medium behavioral effects, the family incomes of those initially in the labor force are estimated to increase by $226.276 million, while the family incomes of those not initially in the labor force are estimated to increase by $93.757 million for a total increase in family income of $320.033 million (column 1).[17] Without behavioral effects, the family incomes of those initially in the labor force increases by the $235.513 million increase in the state EITC supplement (column 2). There is no increase in the family incomes of those not initially in the labor force. On net, the model with no behavioral effects understates the change in family income resulting from an expansion of the NYS EITC by $84.520 million.

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[17] Based on the assumptions specified for persons not in the labor force who enter the labor force in response to the EITC increase a single mother with one child would have a family income of $13,912 and a single mother with two children would have a family income of $16,378 with an expansion of the NYS EITC to 45 percent. With an expansion of the NYS EITC to 45 percent of the federal credit, 7,017 single mothers with one child, and 7,227 single mothers with two children would enter the labor force. Based on the CPS, the average family income in the CPS of a single mother with one child not in the labor force is $8,047 and the average family income of a single mother with two children is $9,124. Taking the difference between average incomes in and out of the labor force and multiplying these values by the respective number of people who enter the labor force yields an aggregate increase in family income of $93.757 million.

2.7. Conclusions

Using a variety of parameters drawn from the labor supply and EITC literature, this paper provides low, medium, and high estimates of the effect of expanding the NYS EITC on employment, hours worked, income, poverty, and the cost of the program. It then compares these estimates with those obtained from a model of the effect of expanding the NYS EITC that omits behavioral effects. Overall, an expansion of the NYS EITC from 30 to 45 percent of the federal credit is estimated to increase employment by between 7,125 and 21,363 single mothers. Hours worked are estimated to decline by between 563,000 hours per year and 5.951 million hours per year for those in the labor force at the time of the expansion, and increase by between 11.635 million and 34.886 million hours for those not in the labor force at the time of the expansion. Therefore, on net, hours worked by New York State residents would increase by between 11.071 million and 28.935 million hours.

Total labor earnings for those in the labor force at the time of the expansion of the credit to 45 percent are estimated to decline by between \$19.775 million and \$155.180 million, or an average \$45 to \$147 per person. But these lost earnings are more than made up by the increased earnings of those who enter the labor force in response to the EITC expansion. On net, labor earnings are estimated to increase by between \$63.413 million and \$94.256 million.

The lower labor earnings of those in the labor force at the time of the EITC expansion are offset by their increased EITC benefit, so that average family income is increased across all specifications when compared to the current 30 percent state supplement. With an expansion to a 45 percent state supplement, average federal and state EITC benefits are estimated to increase by between \$116 and \$347. Combining the change in total EITC benefits with the decrease in labor earnings and other changes in family income, results in an average increase in family income of between $75 and $214.

Those who enter the labor force in response to the EITC expansion receive between $8.638 million and $33.307 million in EITC benefits in addition to their labor earnings of between $83.187 million and $249.436 million. On net, this results in additional benefit payments/costs to New York State of between $247.538 million and $293.601 million.

As a result of the additional labor earnings and EITC benefits, total poverty determined using alternative family income declines from 11.75 percent to between 11.39 percent and 11.23 percent, or by between 68,000 and 98,000 persons, once labor force entrants are included. Moreover, child poverty declines from 15.07 percent to approximately 14.01 percent, as 48,000 children are lifted out of poverty.

These results clearly demonstrate that expanding state EITC supplements will significantly increase the labor force participation of single mothers, the total income of low-income families, and reduce their risk of poverty. The labor supply incentives created by the EITC program will move people not currently in the labor force into the labor force. And it will move workers currently in the phase-in region to work more. This will increase their income via both greater labor earnings and higher EITC payments. Hence each additional dollar of EITC benefits to these families will mean more than a dollar of additional income. Since these are predominantly poor families to begin with, the EITC program has its greatest impact on poor families.

This paper further demonstrates the importance of including behavioral effects in estimating the impact of EITC program changes. Using the medium estimates, an increase in the NYS EITC Supplement from 30 to 45 percent will induce 14,244 more people into the labor force. While it will decrease the hours of work of those in the labor force at the time of enactment by 3.867 million hours, this will be offset by the

23.260 million hours of work by new entrants. Likewise, ignoring behavioral effects will miss the decline of $70.497 million in the earnings of those in the labor market at the time of enactment, but also the more than offsetting $166.312 million increase in the earnings of new labor market entrants.

Behavioral effects also impact the estimated cost of the EITC program. The 14,244 people who were not in the labor force prior to the enactment of the EITC will now be counted as receiving EITC benefits. But benefits will also rise on average for those who were employed because those in the phase-in region will work more and those in the phase-out region will work less.

Taken together, these differences between models with and without behavioral effects suggest that cost-benefit analyses of expanding the EITC program made based on estimates from models without behavioral effects would understate both the costs and benefits of the expansion. Moreover, estimates of the effect of current EITC programs on income and poverty which omit labor supply responses to the program—such as the Census Bureaus Alternative Poverty Estimates— fail to capture the complete impact of the EITC.

This study demonstrates why policy research on the effect of the EITC on income understates both the costs and benefits of EITC expansion when it simply adds the increased value of EITC benefits to existing income. Doing so ignores the fact that the major labor supply response to the EITC is for persons not in the labor force to enter the labor market, and that those currently in the labor market will seek to maximize their EITC benefit, which will disproportionately reduce poverty, as most persons below poverty will be induced to increase their labor earnings.

The extension of the existing simulation framework to state EITC programs and more rigorous analysis of outcomes for those not in the labor force is an innovation to the academic literature. Previous simulations have focused primarily on the effect of an EITC expansion on those currently in the labor force, which, as this paper demonstrates, represents only a fraction of the total effect of the EITC. The use of estimates of the elasticity of labor force participation to net income from previous studies of the EITC to simulate changes in employment is a straightforward yet powerful addition to the existing framework. Moreover, extending the outcomes examined to income, poverty, and costs to the state, which were omitted from previous studies, expands the policy relevance of this literature.

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CHAPTER THREE:
THE IMPACT OF FATNESS ON DISABILITY INSURANCE APPLICATION BY THE NON-ELDERLY*

Abstract

The most commonly used measures of fatness in social science research are body mass index (BMI) and obesity, defined as a BMI greater than or equal to 30. The use of BMI is based on the widespread availability of information on height and weight in social science datasets, rather than the medical accuracy of BMI. In fact, BMI is limited as a predictor of health outcomes by its inability to distinguish fat from muscle. Using Social Security Administration (SSA) administrative records recently linked to National Health and Nutrition Examination Survey (NHANES) III data we determine the value of using more accurate measures of fatness than body mass index to predict an important economic and policy outcome: application for Social Security Disability Insurance (DI). These data provide more accurate outcome and predictor variables than were available in previous research into the association between fatness and disability. Our results indicate that despite the limitations of BMI, it is consistently a significant predictor of future application for DI; though more accurate measures of fatness occasionally perform better as predictors of application. As the measure of fatness that is most predictive of a given outcome appears to vary by the outcome examined, we urge the collection of alternative measures of fatness in social science datasets. We also encourage researchers examining the impact of fatness on social science outcomes of interest to use several measures of fatness where possible.

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3.1. Introduction

Fatness is most commonly measured in the social science literature using body mass index (BMI)—weight in kilograms divided by height in meters squared (U.S. DHHS, 2001; NIH, 1998). BMI's main advantage is that the information needed to calculate it is easy to collect and common in social science datasets. Despite its widespread use, many medical researchers argue that BMI fails to distinguish important physical differences between people with identical BMI levels. In particular, BMI does not distinguish between fat and muscle. They further argue that direct measures of fatness (such as total body fat (TBF) or percent body fat (PBF)) are more accurate (Prentice and Jebb, 2001; Gallagher et al., 1996).

Obesity is a concept that refers to excessive fatness (Bjorntorp, 2002; Bray, Bouchard, and James, 1998). Each of the many measures of obesity has strengths and weaknesses that depend on the measure of fatness on which it is based. For the reasons discussed above, the most common definition of obesity in the social science literature is based on BMI: a BMI greater than or equal to 30.

Obesity may increase the risk of disability (Burkhauser and Cawley, 2005; Lakdawalla, Bhattacharya, and Goldman, 2004; Ferraro et al., 2002; Narbro et al., 1996). However, these studies use BMI (constructed using self-reports of weight and height) as a measure of fatness, and have not tested whether more accurate measures of fatness (such as TBF and PBF) are predictors of these outcomes. This paper evaluates which measure or measures of fatness (specifically, TBF, PBF, BMI, waist circumference, waist-to-hip ratio, or obesity status based on each of these measures of fatness) most accurately predict application for Social Security Disability Insurance (DI) benefits.

Eligibility for DI depends on a determination that the applicant's disability meets or exceeds the medical listing, conditional on attaining the necessary number of covered quarters of employment.[1] Hence we will focus on the decision to apply for benefits, because application and not acceptance is entirely the decision of the individual. We focus on the working age population (ages 21 to 48) for several reasons. We restrict the sample to persons no more than 48 years of age, as we need to observe respondents who are potentially eligible for the DI program for the full 10 years covered by our sample. Moreover, we want to avoid observing older applicants who face the more complicated decision of whether to apply for DI, or take early Old-Age (OA) retirement benefits or other Social Security benefits. We restrict the sample to persons at who are initially at least 21 years of age, as this age group is likely to have achieved the necessary covered quarters of employment for DI eligibility within our 10 year sample period.

Existing research (Burkhauser and Cawley, 2008) shows that how a researcher defines obesity can have significant implications for research. In particular, racial disparities in the prevalence of obesity are dramatically altered by using a more accurate measure of fatness such as Percent Body Fat rather than BMI to define obesity. This research also indicates that the correlation of fatness with employment status differs significantly by the measure of fatness used; for example, decomposing body mass into Total Body Fat and Fat-Free Mass reveals that only Total Body Fat, and never Fat-Free Mass, is correlated with the likelihood of employment. This important difference in body composition is obscured by the use of BMI as a measure of fatness. This paper examines which of the many measures of fatness available in the NHANES III data are most predictive of application for DI benefits, and more generally, are useful for predicting social science outcomes.

[1] To be eligible to receive DI benefits a claimant must have worked in employment covered by the Social Security Program for at least 20 of the previous 40 quarters. Claimants under the age of 31 can qualify for DI benefits by having worked in covered employment in at least half of the quarters that elapsed since the age of 21, with a minimum of 6 covered quarters. Blind claimants under the age of 24 can qualify for DI benefits by having worked in covered employment in at least 6 of the previous 12 quarters (SSA, 2007, Table 2.A7).

3.2. Fatness and Disability Insurance (DI)

To be eligible for DI disability benefits, applicants must, among other things, have medical conditions that meet or exceed the official Listings of Impairments. (See Daly and Burkhauser, 2003 for a discussion of their changing eligibility criteria.) While obesity is no longer a named condition in these listings, several of the medical conditions in the listing are correlated with obesity.

During roughly the same time that the prevalence of obesity (defined using BMI) doubled in the U.S., the employment rate of working-age persons with disabilities fell by 28.4 percent for men and 13.8 percent for women (Stapleton and Burkhauser, 2003). Moreover, the number of beneficiaries receiving income from DI doubled from 3.8 million in 1983 to 7.6 million in 2002 (Social Security Administration, 2004). These simultaneous trends have raised concerns that obesity increases disability-related exits from the labor force. Studies using micro data find that obesity (defined by BMI) is correlated with exit from the work force and with increases in DI rolls (Lakdawalla, Bhattacharya, and Goldman, 2004; Ferraro et al., 2002; Narbro et al., 1996). A substantial literature in economics models the decision of workers to apply for DI following the onset of a disability. (See Bound and Burkhauser, 1999 for a review of the literature and Burkhauser, Butler and Gumus, 2004 for a structural modeling example in this literature.) But data limitations have required the vast majority of these studies to use subjective measures of health such as self-rated work limitations or self-rated health as the measure of disability. In the rare instance when information on fatness was available, it was in the form of self-reported weight (utilized in conjunction with self-reported height, e.g. as BMI).

This paper substantially contributes to the literature on the impact of obesity on the decision to exit the labor market via DI. It makes use of social security records, as opposed to self-reports of disability or receipt of DI benefits, and it examines which of the numerous measures of fatness available in the NHANES III is most predictive of application for DI.

3.3. Background on More Accurate Measures of Fatness

While there is consensus in the medical literature that BMI is a poor measure of fatness (McCarthy et al., 2006; Yusuf et al., 2005; Gallagher et al., 1996; Smalley et al., 1990; Garn et al., 1986), there is no consensus on which of the more accurate measures of fatness is best (Freedman and Perry, 2000). Candidates include: total body fat (TBF), fat free mass (FFM—which is total body mass minus total body fat), percent body fat (PBF—which is total body fat divided by total mass), waist circumference (WC), and waist-to-hip ratio (WHR).

TBF and PBF are appealing measures of fatness because the medical literature suggests that fat is a risk factor for morbidity and mortality (Pi-Sunyer, 2002; U.S. DHHS, 2001). For example, Trayhurn and Beattie (2001) argue that fat directly causes Type II diabetes and cardiovascular disease by secreting resistin and leptin; these findings suggest that TBF may be the most relevant measure of fatness for predicting social science outcomes affected by health because the sheer volume of fat may determine the amount of leptin and resistin released; alternatively PBF may be a better measure if additional fat-free-mass can dilute the health impacts of those secretions.

There are a variety of ways of measuring TBF and therefore PBF, which range from methods that use very expensive equipment that can be used only in a lab setting and which require subject cooperation or exposure to radiation (e.g. magnetic resonance imaging or MRI, dual x-ray absorptiometry or DXA) to more portable (field-based) methods that are less expensive and rapid such as Bioelectrical Impedance Analysis or BIA (Freedman and Perry 2000). Each method of measuring body composition has its pros and cons (Freedman and Perry 2000); for example, the

BIA method of estimating fat-free mass is less accurate for the severely obese (NIH, 1996). However, despite this limitation, the NIH endorses BIA as a useful technique for measuring body fat and body composition generally (NIH 1996). In addition, BIA is arguably the best method to assess fatness for large-scale surveys; Prentice and Jebb (2001) conclude: "Bioimpedance is probably the only technique that can meet the criteria of being simple, rapid, and free from operator variability" (page 146). However, it is not our position that BIA is unambiguously preferable to every other method of measuring body fat; we use it because it is one method endorsed by the NIH (NIH, 1996) and it is the only method for which data is now available in a large, nationally representative U.S. dataset—the NHANES.

Researchers can utilize the full variation in PBF, or they can convert it into an indicator variable for obesity. The NIH classifies a man as obese if his PBF exceeds 25 percent and a woman as obese if her PBF exceeds 30 percent (NIDDK, 2006).

Findings from the medical literature also suggest that it is not just the amount of fat that matters, but also the location or distribution of that fat. In particular, abdominal visceral fat (i.e. that located around the internal organs) is associated with an elevated risk of morbidity (Bray, Bouchard, and James, 1998). The amount of abdominal visceral fat can be assessed using laboratory methods, but in practice it is frequently measured using either waist circumference or waist-to-hip ratio; comparisons have found that these two are highly correlated with abdominal fat (Snijder et al., 2002).

While it is generally accepted that central adiposity (abdominal fat) is associated with greater risk of morbidity and mortality, it is not clear that waist-to-hip ratio is the best way to measure it. For example, a 1998 NIH report recommends the use of waist circumference rather than waist-to-hip ratio to measure central adiposity (NIH, 1998, p. xxiv). One can use estimated waist circumference in isolation as a measure of fatness in social science datasets, or in combination with BMI. The NIH classifies individuals at “high risk” if waist circumference exceeds 102 cm (40 inches) for men or exceeds 88 cm (35 inches) for women (NIH, 1998, p. xv). For waist-to-hip ratios, Han et al. (1995) find an increased prevalence of cardiovascular risk factors if waist-to-hip ratio is greater than or equal to 0.95 for men, or is greater than or equal to 0.80 for women. Hence we also look at waist-to-hip ratios and waist circumference, as well as indicators for being at “high risk” based on the respective measure of central adiposity.

Despite the skepticism in the medical literature toward BMI as a measure of either fatness or obesity, virtually no tests of the robustness of social science-based findings using these more accurate measures of fatness have been undertaken on social science-based outcomes. This paper fills that void

3.4. Multiple Measures of BMI

The inclusion of both measured weight and height, and self-reported weight and height in the NHANES III allows for the calculation of BMI values and corresponding indicators for obesity from measured and self-reported values. Though BMI based on measured weight and height is more accurate than BMI based on self-reported weight and height, we also examine self-reported BMI due to its greater availability in social science data sets.

Previous research by Cawley and Burkhauser (2006) using the NHANES III identified systematic differences between self-reported weight and height and measured weight and height by race and gender. In order to allow researchers using data sets which include only self-reported values to adjust for the self-report bias in weight and height, they provide regression coefficients by sex and race, which can be applied to self-reported weight and height, and age to predict measured weight and height. Given that the convention in economic literature examining BMI is to use these adjustment factors, we also examine adjusted BMI and the corresponding indicator for obesity.

3.5. Data

We estimate our models using the 2006 version of the restricted access National Health and Nutrition Examination Survey (NHANES) III linked Master Beneficiary Record and Mortality files. The NHANES III is a nationally representative cross-sectional survey conducted from 1988 to 1994. All respondents were asked to complete an extensive interview (during which they were asked to report their weight and height) and undergo a subsequent medical examination in a large mobile examination center (during which their weight and height were measured). The NHANES III sample consists of 31,311 examined respondents.

The NHANES III is the "Rosetta Stone" for estimating more accurate measures of fatness, because it is the only large, nationally-representative survey in the United States that includes the data necessary to calculate many measures of fatness. It includes: Bioelectrical Impedance Analysis readings that can be used to calculate fat-free mass and therefore Total Body Fat and Percent Body Fat, skinfold thicknesses that can be used to calculate percent body fat, measured weight and height, self-reported weight and height, measured waist circumference, and measured waist-to-hip ratio. Furthermore, in 2006, DI administrative records data through December 2003 were linked to NHANES III.

The NHANES III linked Social Security Administration (SSA) Master Beneficiary Record (MBR) file contains Old-Age, Survivors, and Disability Insurance (OASDI) eligibility and benefit information on all NHANES III respondents who could be linked to their Social Security records, and applied for OASDI program benefits from 1962 through 2003. The SSA linked NHANES III respondents to their Social Security records using their Social Security Number, name, data of birth, sex, state of birth, and zip code (NCHS, 2006, p. 6). The SSA was able to link over 90 percent of NHANES III respondents to their Social Security records (NCHS, 2006, p. 9).[2]

Unfortunately, the MBR file contains Social Security eligibility information only for those persons who apply for Social Security benefits between 1962 and 2003. It does not contain information on the majority of NHANES respondents who do not file some type of social security claim over the sample period. As we do not have social security records for all persons in the sample, we are unable to identify those persons who have met the covered quarters requirement for DI, but do not apply for DI benefits. That is to say, we are unable to separate the entire sample into those who are insured by the DI program and those who are not insured by the DI program. We must therefore included uninsured persons in our estimation sample.

However, this limitation serves only to bias our results towards zero, suggesting that our estimates represent a lower-bound on the effect of fatness on DI application. We are also limited to examining application for DI within 10 years of the medical examination, as we have at most 10 years of data for respondents examined in 1994. As the MBR file contains only detailed information on the most recent application for DI, we are limited to examining the most recent application for DI benefits, rather than the entire history of DI application. We also lack the Social Security Earnings Records, which would provide more detailed information on all NHANES III respondents over the entire sample period.

[2] The primary reason an NHANES III respondent could not be linked to their Social Security record was refusal by the NHANES III respondent to provide their Social Security Number. Missing data on last name and date of birth also resulted in linkage failures (NCHS, 2006, p. 6).

In addition to the linkage of the NHANES III to Social Security records by the SSA, the National Center for Health Statistics (NCHS) linked the NHANES III to death certificate information found in the National Death Index (NDI) from 1988 through 2000. The use of the NHANES III linked Mortality file allows for the exclusion of respondents who died during the sample period.

We estimate models of application for DI using all NHANES III respondents who were between ages 21 and 48 at the time of their examination, are linked to the administrative records, who were not already recipients of DI benefits, and who did not die within the 5 or 10 year window following their examination. Mexican Americans are also excluded from the sample, because the sample used to generate the BIA conversion equations excluded Hispanics. After these sample restrictions, we have complete data on 2,109 men and 2,412 women for 5 years post-examination, and 2,073 men and 2,387 women for 10 years post-examination.

Table 3.1 presents descriptive statistics for the sample, by gender and application period. As there are few differences between the 5 and 10 years samples only the descriptive statistics for the 5 years sample are discussed here. For men in the 5 year sample, the average age at the time of their medical exam was 414.7 months (34.56 years). For women in the 5 year sample, the average age at the time of their medical exam was 415.2 months (34.60 years). For men, a high school diploma was the highest educational attainment of 36.9 percent of the sample, while 44.0 percent had education beyond high school. For women, 41.0 percent had a high school diploma, while 42.1 percent had education beyond high school. For men, 55.4 percent were married, 6.5 percent were divorced, and 2.8 percent were separated. For women, 51.3 percent were married, 12.2 percent were divorced, and 5.4 percent were separated. 51.4 percent of men in the 5 year sample were non-Hispanic white, and 48.6 percent were non-Hispanic black. For women, 50.8 percent of the 5 year sample was non-Hispanic white, and 49.2 percent was non-Hispanic black. The modal family income category was $10,000 to $19,999, with the median respondent having a family income of $20,000 to $29,999, for both men and women.

Using the BIA method of measuring body fat, the average male in the 5 year sample had 63.5 kg of fat free mass and 19.6 kg of body fat, while the average female had 46.0 kg of fat free mass and 26.1 kg of body fat. For the average male this translates into a PBF of approximately 22.7. For the average female this translates to a PBF of approximately 34.5. The PBF calculated using skinfold thicknesses was considerably lower at 13.7 for males and 29.2 for females. The average PFFM from BIA was 77.3 for men, and 65.5 for women.

Using measured height and weight, the average male in the 5 year sample had a BMI of 26.4, while the average female had a BMI of 26.9. There were minimal differences between the average BMI values calculated using either measured height and weight, self-reported height and weight, or adjusted self-reported height and weight.

The average male in the 5 year sample had a waist circumference of 92.2 cm, while the average female had a waist circumference of 87.7 cm. When waist circumference is dichotomized into an indicator for excessive fatness, 19.8 percent of males and 41.6 percent of females are classified as "high risk" (WC>102 cm for men, WC>88 cm for women).

The waist-to-hip ratio of the average male in the 5 year sample was 0.922, and 0.844 for the average female. Dichotomizing waist-to-hip ratio into an indicator for excessive fatness, 29.9 percent of males and 72.4 percent of females are classified as "high risk" (WHR≥ 0.95 for men, WHR≥ 0.85 cm for women).

Table 3.1. Descriptive statistics for Sample

Variables:	Mean (Standard deviation)			
	Men		Women	
	Application for DI within:		Application for DI within:	
	5 years	10 years	5 years	10 years
Age in Months at Exam	414.737	413.450	415.227	414.738
	(92.455)	(92.163)	(89.732)	(89.687)
High School	0.369	0.368	0.410	0.410
	(0.483)	(0.482)	(0.492)	(0.492)
Greater than High School	0.440	0.445	0.421	0.422
	(0.497)	(0.497)	(0.494)	(0.494)
Married	0.554	0.555	0.513	0.516
	(0.497)	(0.497)	(0.500)	(0.500)
Divorced	0.065	0.066	0.122	0.120
	(0.247)	(0.248)	(0.328)	(0.325)
Separated	0.028	0.027	0.054	0.054
	(0.166)	(0.162)	(0.226)	(0.227)
White	0.514	0.517	0.508	0.509
	(0.500)	(0.500)	(0.500)	(0.500)
Black	0.486	0.483	0.492	0.491
	(0.500)	(0.500)	(0.500)	(0.500)
Family Income from $0 to $9,999	0.115	0.110	0.158	0.156
	(0.319)	(0.313)	(0.364)	(0.363)
Family Income from $10,000 to $19,999	0.230	0.231	0.223	0.222
	(0.421)	(0.422)	(0.416)	(0.416)
Family Income from $20,000 to $29,999	0.174	0.175	0.170	0.170
	(0.380)	(0.380)	(0.376)	(0.376)
Family Income from $30,000 to $39,999	0.163	0.164	0.138	0.138
	(0.370)	(0.371)	(0.345)	(0.345)
Family Income from $40,000 to $49,999	0.125	0.123	0.121	0.122
	(0.330)	(0.329)	(0.327)	(0.328)
Family Income >$50,000	0.193	0.196	0.190	0.191
	(0.395)	(0.397)	(0.393)	(0.394)
Fat Free Mass	63.518	63.492	46.049	45.995
	(10.285)	(10.263)	(7.374)	(7.353)
Total Body Fat	19.608	19.600	26.083	26.010
	(9.456)	(9.397)	(12.415)	(12.395)

Table 3.1. (Continued)

	Mean (Standard deviation)			
	Men		Women	
	Application for DI within:		Application for DI within:	
Variables:	5 years	10 years	5 years	10 years
Percent Body Fat (PBF)	22.686	22.699	34.467	34.430
	(6.697)	(6.649)	(8.011)	(8.012)
Percent Body Fat (Skinfold)	13.726	13.691	29.189	29.122
	(11.199)	(11.146)	(14.814)	(14.811)
Percent Fat Free Mass	77.314	77.301	65.533	65.570
	(6.697)	(6.649)	(8.011)	(8.012)
Body Mass Index (Measured)	26.369	26.359	26.873	26.834
	(5.078)	(5.050)	(6.820)	(6.808)
Body Mass Index (Self-reported)	26.222	26.205	26.244	26.200
	(4.499)	(4.476)	(6.167)	(6.149)
Body Mass Index (Self-reported, Adjusted)	26.284	26.265	26.935	26.887
	(4.838)	(4.813)	(6.491)	(6.471)
Waist Circumference (WC)	92.175	92.126	87.681	87.565
	(13.725)	(13.656)	(15.847)	(15.811)
Waist-to-Hip Ratio (WHR)	0.922	0.921	0.844	0.843
	(0.068)	(0.068)	(0.077)	(0.077)
Obese PBF	0.369	0.370	0.702	0.700
	(0.483)	(0.483)	(0.458)	(0.458)
Obese Skinfold	0.164	0.162	0.523	0.521
	(0.370)	(0.368)	(0.500)	(0.500)
Obese BMI Measured	0.189	0.187	0.269	0.267
	(0.391)	(0.390)	(0.444)	(0.442)
Obese BMI Self-reported	0.156	0.154	0.224	0.221
	(0.363)	(0.361)	(0.417)	(0.415)
Obese BMI Self-reported, Adjusted	0.169	0.168	0.261	0.258
	(0.375)	(0.374)	(0.439)	(0.437)
High Risk WC	0.198	0.196	0.416	0.413
	(0.398)	(0.397)	(0.493)	(0.492)
High Risk WHR	0.299	0.298	0.724	0.721
	(0.458)	(0.457)	(0.447)	(0.448)
Applied for DI	0.033	0.071	0.029	0.067
	(0.178)	(0.257)	(0.168)	(0.251)
Sample Size	2109	2073	2412	2387

Based on PBF from BIA, 36.9 percent of men in the 5 year sample were classified as obese, while 70.2 percent of women were classified as obese (PBF>25 for men, PBF>30 for women). Based on measured BMI, 18.9 percent of men in the 5 year sample were classified as obese, while 26.9 percent of women were classified as obese (BMI $\geq$ 30). The much lower prevalence of obesity when calculated using BMI relative to PBF is consistent with the results of Burkhauser and Cawley (2008).

3.6. Method of Calculating Total Body Fat (TBF) and Percent Body Fat (PBF)

We calculate TBF and PBF using BIA measurements contained in the NHANES III. There are multiple systems used to collect BIA data, which generate output in different scales; however, the output is easily converted between scales. In NHANES III, BIA resistance is measured using a Valhalla system, while in the study that produced the prediction equations (Sun et al., 2003), resistance is measured using an RJL system. In order to use the Sun et al. (2003) prediction equations, we first convert the Valhalla BIA resistance value for each NHANES III respondent to the equivalent RJL resistance value using the formulas contained in the appendix to Chumlea et al. (2002):

For males:

$$\text{RJL resistance} = 2.5 + 0.98 \text{ Val resistance}$$

For females:

$$\text{RJL resistance} = 9.6 + 0.96 \text{ Val resistance}$$

Chumlea et al. (2002) report that the R-squared was .996 for men and .993 for women.

Sun et al. (2003) use data from five research centers to establish the equations to predict fat-free mass using BIA resistance measurements. TBF was determined using measurements of total body water, bone mineral content, and body density. Fat-free mass (FFM) was calculated as weight minus TBF. They find the following equations had the best fit:

For males:

$$\text{Fat-free mass} = -10.678 + 0.262\ \text{weight} + 0.652\,\frac{\text{Stature}^2}{\text{Resistance}} + 0.015\ \text{Resistance}$$

For females:

$$\text{Fat-free mass} = -9.529 + 0.168\ \text{weight} + 0.696\ \frac{\text{Stature}^2}{\text{Resistance}} + 0.016\ \text{Resistance}$$

Weight was measured in kilograms and stature (height) in centimeters. These formulas for calculating fat and fat-free mass do not control for age because when Sun et al. (2003) tested whether age should be included, they found it did not significantly improve the fit of their model. The same formula is used for African Americans and whites because Sun et al. (2003) found no significant differences in goodness of fit of their model whether they pooled whites and African Americans or used whites alone; for this reason, they report only equations derived from whites and African Americans pooled. However, Sun et al. (2003) note that the final FFM equations (which do not control for race) tend to *under*predict African American males' FFM by 2.1 kg and African American females' FFM by 1.6 kg, and to *over*predict white males' FFM by 0.4 kg and white females' FFM by 0.3 kg. (No Hispanics were in the sample.) We adjust the FFM of NHANES respondents by these amounts. The R-squared of the prediction equation was .90 for men and .83 for women.

BIA predicts FFM, but TBF is easily determined using the same identity below for men and women:

$$\text{Total body fat} = \text{weight} - \text{fat-free mass}$$

and:

$$\text{Percent body fat} = (\text{Total body fat} / \text{weight}) * 100$$

The NHANES III also includes measurements of tricep and subscapular skinfold thicknesses. These skinfold measures can be converted into percent body fat following a two-step process. First, body density is predicted using tricep and subscapular skinfold thicknesses based on the age and gender specific formulas provided in Durnin and Womersley (1974). Second, percent body fat was computed using body density using the Siri (1956) conversion equation:

$$PBF = \left(\frac{4.95}{density} - 4.50 \right) * 100$$

The value in examining PBF calculated using skinfolds in addition to PBF calculated from BIA is that tricep and subscapular skinfold thicknesses are the only measure of fatness consistently collected in the NHANES other than BMI.

3.7. Models to Estimate the Correlation of Fatness with Application for DI Benefits

Various measures of fatness serve as our key regressors in models in which the dependent variable is an indicator for whether the NHANES III respondent applied for DI benefits within 5 years or 10 years of their NHANES III physical examination.

Application for DI is determined using the Master Beneficiary Record File. Application for DI benefits within 5 years or 10 years of the physical examination is determined in the following manner. First, the sample is restricted to respondents ages 21 to 48 at the time of their physical examination, and those persons who die within 5 years or 10 years of their medical exam are dropped from the sample. Next, the date on which the remaining respondents most recently filled for DI benefits must have been within either 5 years or 10 years after their physical examination. Their Beneficiary Identification code (BIC) at their date of current eligibility for benefits must have been coded "primary claimant/number holder" and their type of claim

(TOC) had to be “disability care where beneficiary is: a) disabled primary not reduced for age; b)aged or divorced wife/husband not reduced for age; c) young wife entitled for young child-in-care; d) young child” or “disability case where beneficiary is: a) disabled primary reduced for age; b) aged or divorced wife/husband reduced for age”.

We include both applicants who received DI benefits and those who were denied DI benefits in our sample. We can identify whether or not an applicant was denied benefits, and the reason for that denial, based on the variable Ledger Account File (LAF). Reasons for denial include failing to meet the medical listings for disability, or having insufficient covered quarters of employment (uninsured). In our 5 year sample, 3 men and 6 women were denied benefits due to being uninsured, while 28 men and 19 women were denied benefits due to not meeting the medical listings out of a total of 69 applications for men and 70 applications for women. In our 10 year sample, 10 men and 21 women were denied benefits due to being uninsured, while 55 men and 51 women were denied benefits due to not meeting the medical listings out of a total of 147 applications for men and 161 applications for women.[3]

We assume that individual i applies for DI benefits if his health H_i falls below some critical limit H^*. Health is assumed to be a function of fatness F_i and other characteristics X_i. Specifically:

$$H_i = F_i \beta + X_i \delta + u_i$$

Health H is not observed, but we know whether an individual applies for DI benefits; we denote $DI\_app=1$ if individual i applies for DI benefits and $DI\_app=0$ otherwise. Formally, applying for DI benefits relates to latent health in the following way:

$$DI\_app_i = 0 \text{ if } H_i \geq H^* \text{ or } DI\_app_i = 1 \text{ if } H_i < H^*$$

[3] Estimates were also obtained for a sample which excluded persons denied coverage on the basis of being uninsured. This had no significant effect on the coefficient estimates.

Normalizing H^* at $H=0$, the probability that one applies for DI benefits is equal to the following.

$$\text{(1)} \qquad \Pr[\text{DI\_app}_i = 1 \mid F_i, X_i] = \Pr[u_i < -F_i\beta - X_i\delta]$$

With certain assumptions about the distribution of the error term u, one can estimate the probability of applying for DI benefits as a function of fatness F and characteristics X using probit regression.

We estimate model (1) for the following measures of fatness: total body fat and fat-free mass from BIA, percent body fat from BIA, percent fat-free mass from BIA, percent body fat from skinfolds, body mass index from measured weight and height, body mass index from self-reported weight and height, body mass index from adjusted self-reported weight and height, waist circumference, waist-to-hip ratio, and indicators for obesity based on each measure of fatness. Control variables include: age and age squared at time of NHANES III examination, race, education category, marital status, family income to poverty cut-off ratio, and family income category. Models are estimated separately for men and women.

Our set of control variables includes regressors that may themselves be determined by fatness. As such, models are first estimated which include only those variables which are completely exogenous: age and race. We subsequently estimate models which add education, marital status, and family income to poverty cut-off ratio. By excluding variables which are potentially determined by fatness, we measure the total correlation of fatness with DI application. By then including these controls, we can determine the extent to which the correlation of fatness with DI application operates through these variables. Lastly, we estimate models which add family income category. Likewise, by excluding income category, we measure the total correlation of fatness with DI application, and by then including income category we can determine the extent to which the correlation may operate through income. Income may prove to be a relevant pathway because previous research has determined that for white females, weight and obesity lower wages (Cawley, 2004).

We take into account the complex survey design of the NHANES III by estimating our models using svy commands in Stata version 10 that account for the strata and primary sampling units of the NHANES III. And we use the WTPFEX6 sample weights, which are recommended when studying medical examination variables such as weight and BIA measurements.

3.8. Results

We first estimate probit models of application for DI benefits within 5 years or 10 years of the medical examination, which only control for the exogenous variables age at time of NHANES III examination and race.[4] These models are estimated for each of our measures of fatness, and corresponding indicators for excessive fatness. Table 3.2 presents results from the probit models for DI application by sex and application time period. For application by males within 5 years none of the measures of fatness are statistically significant predictors of application for DI. Moreover, the coefficients on BMI, BMI (self-reported), WHR, obese (BMI), obese (BMI self-reported)), high-risk WC, and high-risk WHR have the expected signs. The coefficients on TBF, FFM, PBF (BIA), PBF (skinfold), PFFM, BMI (self-reported, adjusted), WC, obese PBF (BIA), and obese PBF (skinfold) have the opposite sign from what was expected.

When the time for men to apply for DI is extended to 10 years from the time of the medical examination all three continuous measures of BMI have the expected signs, and become statistically significant at the 10 percent level. A one unit increase in measured BMI is associated with a 0.27 percentage point increase in the probability

[4] Models were estimated with two different sets of controls for age. In the first specification age and age squared were included as regressors. In the second specification indicators for age at time of exam were used. The two specifications yield nearly identical results, and so we report only the results for the specification including age and age squared in this paper.

of applying for DI within 10 years. Obesity based on measured BMI is now statistically significant at the 10 percent level, and the two obesity measures based self-reported BMI are significant at the 5 percent level. Being obese by measured BMI at the time of the medical exam is estimated to increase the probability of applying for DI benefits within 10 years by approximately 3.86 percentage points. Obesity based on self-reported weight and height is estimated to increase the probability of applying for DI benefits within 10 years by 6.75 percentage points. Obesity based on self-reported weight and height adjusted using the Cawley and Burkhauser (2006) method is estimated to increases the probability of applying for DI benefits within 10 years by 5.26 percentage points. The coefficients on WC and obese PBF (skinfold) now have the expected signs, though they remain insignificant.

Table 3.2. Social Security Disability Insurance Application Probits for Persons Ages 21 to 48

	Men		Women	
	Application for DI within:		Application for DI within:	
Measure of Fatness:	5 years	10 years	5 years	10 years
Total Body Fat (w/ Fat Free Mass)	-0.00128	-0.00028	0.00095	0.00243**
	(-1.23)	(-0.19)	(1.35)	(2.61)
	[0.93694]	[0.87747]	[0.94362]	[0.88814]
Fat Free Mass (w/ Total Body Fat)	0.00057	0.00125	-0.00025	-0.00193
	(0.72)	(1.15)	(-0.23)	(-0.95)
	[0.93694]	[0.87747]	[0.94362]	[0.88814]
Percent Body Fat (BIA)	-0.00173	-0.00136	0.00107	0.00218**
	(-1.44)	(-0.77)	(1.14)	(2.27)
	[0.93978]	[0.87940]	[0.94527]	[0.88982]
Percent Body Fat (skinfold)	-0.00050	-0.00029	0.00052	0.00104**
	(-0.70)	(-0.36)	(1.40)	(2.10)
	[0.93883]	[0.87410]	[0.94610]	[0.88647]
Percent Fat Free Mass	0.00173	0.00136	-0.00107	-0.00218**
	(1.44)	(0.77)	(-1.15)	(-2.27)
	[0.93978]	[0.87940]	[0.94527]	[0.88982]
Body Mass Index (measured)	0.00001	0.00266*	0.00152**	0.00301***
	(0.0039)	(1.71)	(2.12)	(3.38)
	[0.93694]	[0.87747]	[0.94486]	[0.88689]

Coefficients are marginal effects. t-statistics in parentheses. Percent of applicants correctly predicted in brackets. *p< 0.10, **p< 0.05, and ***p< 0.01. The models also include age at exam, age at exam squared, and race.

Table 3.2. (Continued)

	Men		Women	
	Application for DI within:		Application for DI within:	
Measure of Fatness:	5 years	10 years	5 years	10 years
Body Mass Index (self-reported)	0.00003	0.00309*	0.00141**	0.00302***
	(0.016)	(1.87)	(2.13)	(2.91)
	[0.93599]	[0.87554]	[0.94527]	[0.88689]
Body Mass Index (self-reported, adjusted)	-0.00005	0.00291*	0.00134**	0.00278***
	(-0.036)	(1.91)	(2.07)	(2.74)
	[0.93694]	[0.87651]	[0.94527]	[0.88605]
Waist Circumference	-0.00020	0.00072	0.00093***	0.00145***
	(-0.31)	(1.14)	(3.26)	(3.18)
	[0.93883]	[0.87410]	[0.94403]	[0.89024]
Waist-to-Hip Ratio	0.00369	0.15714	0.11584**	0.17119**
	(0.038)	(1.14)	(2.14)	(2.03)
	[0.93694]	[0.87699]	[0.94610]	[0.88898]
Obese by PBF (BIA)	-0.00132	-0.00060	0.01585	0.02125
	(-0.11)	(-0.044)	(1.34)	(1.40)
	[0.93694]	[0.87603]	[0.94652]	[0.88563]
Obese by PBF (skinfold)	-0.00989	0.01607	0.01326	0.02405*
	(-0.92)	(0.88)	(1.28)	(1.91)
	[0.93789]	[0.87506]	[0.94403]	[0.88689]
Obese by BMI (measured)	0.01761	0.03860*	0.02171*	0.04809***
	(0.81)	(1.84)	(1.81)	(3.13)
	[0.93646]	[0.87795]	[0.94610]	[0.89108]
Obese by BMI (self-reported)	0.03646	0.06745**	0.02777**	0.05993***
	(1.36)	(2.48)	(2.07)	(3.15)
	[0.93646]	[0.88037]	[0.94610]	[0.88856]
Obese by BMI (self-reported, adjusted)	0.02492	0.05261**	0.01964*	0.04637***
	(1.04)	(2.03)	(1.76)	(2.84)
	[0.93741]	[0.88037]	[0.94610]	[0.88940]
High Risk WC	0.00716	0.02834	0.03208***	0.04033***
	(0.36)	(1.22)	(2.94)	(3.17)
	[0.93599]	[0.87699]	[0.94279]	[0.88689]
High Risk WHR	0.00323	0.01806	0.01462	0.00953
	(0.18)	(0.99)	(1.26)	(0.63)
	[0.93646]	[0.87554]	[0.94527]	[0.89191]
Number of Applications	69	147	70	161
Sample Size	2109	2073	2412	2387

As an alternative method of assessing the relative predictive power of the various measures of fatness, the percent of persons correctly classified as applicants or non-applicants was also calculated. Despite the measures of fatness based on PBF from BIA being statistically insignificant, they generally outperform the other measures of fatness in terms of correctly predicting application for DI benefits. In the men 5 year case, PBF correctly classified the greatest portion of the sample at 93.98 percent. In the men 10 year case, obese based on self-reported weight and height correctly classified the greatest portion of the sample at 88.0 percent.

Results from the models for female application for DI benefits within 5 years of the medical examination suggest that fatness is more predictive of DI application by women. As shown in Table 3.2, all the coefficients have the expected sign. All three continuous measures of BMI are significant at the 5 percent level, as is obesity from self-reported BMI. Obesity from measured BMI and self-reported adjusted BMI are significant at the 10 percent level. A one unit increase in measured BMI is associated with a 0.15 percentage point increase in the probability of applying for DI within 5 years. Being classified as obese by measured BMI is estimated to increase the probability of DI application within 5 years by 2.17 percentage points.

The more medically accurate WC is significant at the 1 percent level, as is and being classified as high-risk based on WC. A one unit increase in WC is associated with a 0.09 percentage point increase in the probability of applying for DI within 5 years. Being classified as high-risk based on WC is associated with a 3.21 percentage point increase in the probability of DI application within 5 years. WHR is significant at the 5 percent level, and a one percentage point increase in WHR increases the probability of DI application within 5 years by 0.12 percentage points.

The association between fatness and DI application by women is even stronger in the 10 year sample. All coefficients continue to have the correct sign, and only FFM, obese PBF (BIA and skinfold), and high risk WHR are not significant. Of the 17 measures of fatness, 9 are significant at the 1 percent level. Again focusing on BMI, a one unit increase in measured BMI is associated with a 0.30 percentage point increase in the probability of applying for DI within 10 years. Being classified as obese by measured BMI is estimated to increase the probability of DI application within 10 years by 4.81 percentage points.

For women, the various measures of fatness correctly classify those who apply for benefits at approximately the same rate. In the 5 year sample, obese based on BIA correctly classifies the greatest portion of the sample at 94.7 percent. However, at 10 years high risk WHR correctly classifies the greatest portion of the sample at 89.19 percent.

We next estimate models of DI application which add controls for education, marital status, and income to poverty ratio to the previous controls age at exam and race. These results are presented in Table 3.3. With the inclusion of the additional controls, all the fatness coefficients for DI application by men within 5 years of their medical exam remain insignificant. Moreover, only measured BMI, all three BMI based obesity measures, and high-risk WC retain the expected sign.

For men applying for DI within 10 years of their medical examination, the estimates from the models which add controls for education, marital status, and income to poverty ratio are not statistically different from the coefficient estimates obtain from the model with only age and race. All three continuous measures of BMI remain significant at the 10 percent level. Only obese based on self-reported BMI or obese based on self-reported adjusted BMI are significant at the 5 percent level.

Controlling for education, marital status, and income to poverty ratio appears to have more of an effect on the estimates for women. In terms of application for DI within 5 years, only 3 of the 9 measures of fatness that were originally significant remain statistically significant. The remaining three include measured BMI, WC, and high-risk WC. The effect of education, marital status, and income to poverty ratio on the fatness coefficient estimates dissipates considerably in the 10 year application sample, with only WHR and obese (skinfold) reduced to insignificance.

Table 3.3. Social Security Disability Insurance Application Probits for Persons Ages 21 to 48, with Education and Marital Status

	Men		Women	
	Application for DI within:		Application for DI within:	
Measure of Fatness:	5 years	10 years	5 years	10 years
Total Body Fat (w/ Fat Free Mass)	-0.00136	-0.00073	0.00064	0.00198**
	(-1.35)	(-0.51)	(0.95)	(2.35)
	[0.93883]	[0.87844]	[0.94693]	[0.89568]
Fat Free Mass (w/ Total Body Fat)	0.00082	0.00198*	0.00017	-0.00116
	(1.01)	(1.81)	(0.18)	(-0.68)
	[0.93883]	[0.87844]	[0.94693]	[0.89568]
Percent Body Fat (BIA)	-0.00172	-0.00130	0.00088	0.00193**
	(-1.51)	(-0.78)	(0.95)	(2.02)
	[0.94026]	[0.87892]	[0.94693]	[0.89401]
Percent Body Fat (skinfold)	-0.00042	0.00009	0.00041	0.00092*
	(-0.68)	(0.12)	(1.19)	(1.86)
	[0.93883]	[0.87603]	[0.94693]	[0.89359]
Percent Fat Free Mass	0.00172	0.00130	-0.00088	-0.00193**
	(1.51)	(0.78)	(-0.95)	(-2.02)
	[0.94026]	[0.87892]	[0.94693]	[0.89401]
Body Mass Index (measured)	0.00002	0.00261*	0.00125*	0.00268***
	(0.013)	(1.95)	(1.69)	(2.84)
	[0.93694]	[0.87603]	[0.94610]	[0.89275]
Body Mass Index (self-reported)	-0.00017	0.00259*	0.00102	0.00254**
	(-0.13)	(1.74)	(1.49)	(2.31)
	[0.93694]	[0.87603]	[0.94776]	[0.89527]
Body Mass Index	-0.00018	0.00257*	0.00100	0.00238**
(self-reported, adjusted)	(-0.15)	(1.88)	(1.49)	(2.24)
	[0.93789]	[0.87506]	[0.94776]	[0.89485]
Waist Circumference	-0.00020	0.00068	0.00078**	0.00125**
	(-0.38)	(1.20)	(2.50)	(2.53)
	[0.93883]	[0.87410]	[0.94486]	[0.89443]
Waist-to-Hip Ratio	-0.04693	0.01469	0.08214	0.10516
	(-0.51)	(0.11)	(1.44)	(1.05)
	[0.93883]	[0.87603]	[0.94693]	[0.89401]
Obese by PBF (BIA)	-0.00150	-0.00159	0.01617	0.02206
	(-0.13)	(-0.11)	(1.35)	(1.45)
	[0.93599]	[0.87603]	[0.94693]	[0.89317]
Obese by PBF (skinfold)	-0.00996	0.01608	0.01075	0.02076
	(-0.94)	(0.86)	(1.02)	(1.58)
	[0.93789]	[0.87506]	[0.94610]	[0.89485]

Coefficients are marginal effects. t-statistics in parentheses. Percent of applicants correctly predicted in brackets. **p*< 0.10, ***p*< 0.05, and ****p*< 0.01. The models also include education, age at exam, age at exam squared, marital status, race, and family income-to-poverty ratio.

Table 3.3. (Continued)

	Men		Women	
	Application for DI within:		Application for DI within:	
Measure of Fatness:	5 years	10 years	5 years	10 years
Obese by BMI (measured)	0.01741	0.03607*	0.01494	0.03742**
	(0.95)	(1.93)	(1.34)	(2.49)
	[0.93694]	[0.87410]	[0.94693]	[0.89527]
Obese by BMI (self-reported)	0.03340	0.05890**	0.01880	0.04681**
	(1.45)	(2.46)	(1.61)	(2.63)
	[0.93599]	[0.87699]	[0.94693]	[0.89359]
Obese by BMI (self-reported, adjusted)	0.02232	0.04615*	0.01322	0.03655**
	(1.07)	(1.99)	(1.30)	(2.29)
	[0.93599]	[0.87603]	[0.94610]	[0.89401]
High Risk WC	0.00667	0.02514	0.02754**	0.03273**
	(0.40)	(1.22)	(2.39)	(2.45)
	[0.93694]	[0.87410]	[0.94569]	[0.89401]
High Risk WHR	-0.00219	0.00263	0.00936	-0.00549
	(-0.13)	(0.16)	(0.70)	(-0.34)
	[0.93694]	[0.87603]	[0.94610]	[0.89778]
Number of Applications	69	147	70	161
Sample Size	2109	2073	2412	2387

Lastly, we estimate models which add family income as a regressor. By adding income to the model we can estimate the extent to which the effect of fatness on disability application operates through income. Table 3.4 presents results from models of DI application which include family income in addition to the previous demographic characteristics. For both men and women in either the 5 year or 10 year sample the addition of income to the model does not significantly affect any of the coefficient estimates. For men, BMI and obesity based on BMI continue to stand out as strong predictors of future application for DI benefits. A one unit increase in measured BMI is associated with a 0.27 percentage point increase in the probability of applying for DI within 10 years, while being classified as obese by measured BMI is estimated to increase the probability of DI application within 10 years by 3.89 percentage points.

For women, WC and BMI, either continuous or as indicators for excessive fatness, remain strong predictors of future application for DI benefits. A one unit increase in WC is associated with a 0.12 percentage point increase in the probability of applying for DI within 10 years, while being classified as high-risk based on WC is associated with a 2.98 percentage point increase in the probability of DI application within 10 years. A one unit increase in measured BMI is associated with a 0.26 percentage point increase in the probability of applying for DI within 10 years, while being classified as obese by measured BMI is estimated to increase the probability of DI application within 10 years by 3.57 percentage points.

Table 3.4. Social Security Disability Insurance Application Probits for Persons Ages 21 to 48, with Family Income

	Men		Women	
	Application for DI within:		Application for DI within:	
Measure of Fatness:	5 years	10 years	5 years	10 years
Total Body Fat (w/ Fat Free Mass)	-0.00137	-0.00058	0.00055	0.00185**
	(-1.38)	(-0.42)	(0.83)	(2.27)
	[0.93741]	[0.88037]	[0.94237]	[0.89233]
Fat Free Mass (w/ Total Body Fat)	0.00083	0.00190*	0.00021	-0.00108
	(1.08)	(1.79)	(0.22)	(-0.63)
	[0.93741]	[0.88037]	[0.94237]	[0.89233]
Percent Body Fat (BIA)	-0.00172	-0.00117	0.00074	0.00179*
	(-1.53)	(-0.70)	(0.83)	(1.90)
	[0.93741]	[0.88278]	[0.94403]	[0.89359]
Percent Body Fat (skinfold)	-0.00039	0.00019	0.00036	0.00086*
	(-0.62)	(0.25)	(1.05)	(1.74)
	[0.93551]	[0.87892]	[0.94403]	[0.89317]
Percent Fat Free Mass	0.00172	0.00117	-0.00074	-0.00179*
	(1.53)	(0.70)	(-0.83)	(-1.90)
	[0.93741]	[0.88278]	[0.94403]	[0.89359]

Coefficients are marginal effects. t-statistics in parentheses. Percent of applicants correctly predicted in brackets. *p< 0.10, **p< 0.05, and ***p< 0.01. The models also include education, age at exam, age at exam squared, marital status, race, family income-to-poverty ratio, and family income category.

Table 3.4. (Continued)

	Men		Women	
	Application for DI within:		Application for DI within:	
Measure of Fatness:	5 years	10 years	5 years	10 years
Body Mass Index (measured)	0.00001	0.00271*	0.00115	0.00257**
	(0.0056)	(1.98)	(1.53)	(2.66)
	[0.93694]	[0.87892]	[0.94237]	[0.89233]
Body Mass Index (self-reported)	-0.00021	0.00268*	0.00083	0.00240**
	(-0.17)	(1.78)	(1.18)	(2.11)
	[0.93694]	[0.87988]	[0.94237]	[0.89401]
Body Mass Index	-0.00022	0.00267*	0.00080	0.00223**
(self-reported, adjusted)	(-0.18)	(1.93)	(1.18)	(2.03)
	[0.93694]	[0.87988]	[0.94237]	[0.89317]
Waist Circumference	-0.00018	0.00075	0.00074**	0.00119**
	(-0.35)	(1.31)	(2.37)	(2.37)
	[0.93504]	[0.87892]	[0.94444]	[0.89108]
Waist-to-Hip Ratio	-0.04551	0.02871	0.07176	0.09795
	(-0.50)	(0.22)	(1.40)	(1.02)
	[0.93504]	[0.87892]	[0.94403]	[0.89778]
Obese by PBF (BIA)	-0.00078	0.00052	0.01478	0.02102
	(-0.068)	(0.035)	(1.22)	(1.42)
	[0.93694]	[0.87892]	[0.94486]	[0.89359]
Obese by PBF (skinfold)	-0.00967	0.01591	0.00907	0.01940
	(-0.90)	(0.85)	(0.88)	(1.52)
	[0.93694]	[0.87988]	[0.94403]	[0.89527]
Obese by BMI (measured)	0.01786	0.03886*	0.01487	0.03567**
	(1.01)	(2.00)	(1.29)	(2.33)
	[0.93504]	[0.87603]	[0.94154]	[0.89401]
Obese by BMI (self-reported)	0.03184	0.05968**	0.01675	0.04446**
	(1.45)	(2.49)	(1.39)	(2.47)
	[0.93409]	[0.87603]	[0.94237]	[0.89401]
Obese by BMI	0.02064	0.04613*	0.01229	0.03508**
(self-reported, adjusted)	(1.04)	(1.99)	(1.12)	(2.16)
	[0.93504]	[0.87506]	[0.94320]	[0.89317]
High Risk WC	0.00741	0.02629	0.02583**	0.02984**
	(0.45)	(1.23)	(2.21)	(2.28)
	[0.93504]	[0.87699]	[0.94362]	[0.89485]
High Risk WHR	-0.00215	0.00458	0.01177	-0.00388
	(-0.14)	(0.26)	(0.94)	(-0.23)
	[0.93599]	[0.87795]	[0.94486]	[0.89736]
Number of Applications	69	147	70	161
Sample Size	2109	2073	2412	2387

3.9. Discussion

The existing research into the impact of fatness on disability has consistently found that obesity, measured using BMI, increases the probability that a respondent reports themselves as disabled or receiving DI benefits (Ferraro et al., 2002; Burkhauser and Cawley, 2005). This paper builds on the previous literature by demonstrating that BMI based obesity is a significant predictor of future application for DI benefits for both men and women: the underlying policy outcome of interest in this literature. Moreover, it suggests that the use of alternative measures of fatness, mainly percent body fat from BIA and waist circumference, may more accurately predict future DI application, particularly for women.

Previous literature has suggested that BMI is a poor measure of true fatness (Burkhauser and Cawley, 2008), and is less able to predict negative health outcomes than more accurate measures of fatness (Kragelund, 2005; Yusuf et al., 2005). Despite these limitations, the results presented in this paper suggest that BMI is consistently a significant predictor of at least one outcome of policy interest: future application for DI by both men and women. However, sensitivity tests examining alternative outcomes such as current employment and future mortality, suggest that BMI performs less well at predicting these outcomes than alternative measures of fatness.[5]

As suggested in Burkhauser and Cawley (2008), it appears that the measure of fatness that is most predictive of outcomes of interest to social scientists depends on the specific outcome examined. The results presented in this paper further suggest that the relative predictive power of various measures of fatness varies between men and women, even when the same outcome is examined. Therefore, research into the impact of fatness on various outcomes would benefit from wider availability of alternative measures of fatness in the data sets most commonly used by social scientists. Waist

[5] Results from these sensitivity tests are not included in this paper, but are available from the authors upon request.

circumference appears to be a particularly good alternative to BMI as a measure of fatness. However, as BMI is generally predictive of all outcomes of interest, the findings of this paper, and other research, should in no way discourage the use of BMI and BMI based obesity in future research. Rather, it should encourage researchers to add alternative measures of fatness to their analysis whenever possible.

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