The Effects of SCHIP Expansions on Family Structure

By
Jeffrey K. Lee
Duke University
Durham, NC

Honors thesis submitted in partial fulfillment of the requirements for Graduation with Distinction in Economics in Trinity College of Duke University

April 2006

Acknowledgements

The comments and assistance of several individuals were indispensable in the completion of this research project. I would like to thank Brenda Krause of the National Governor's Association for his expertise on Medicaid and SCHIP legislation, and for providing me with reliable data on state health insurance coverage levels for my period of analysis. I would also like to thank Aaron Yelowitz of the University of Kentucky and Christopher Conover of Duke University for their suggestions and advice in the initial stages of the project. I am also grateful for the careful critique that my friends and colleagues have given me, especially the contributions of Veronica Delgado, Sabrina Chen, John Vickery, and Danielle Schwalbach. Additionally, I am very thankful for the technical support of Joel Herndon and Karl Boulaware, and the extensive editing advice provided by Nathan Hensley.

Finally, I would like to thank my advisor Marjorie McElroy, whose value in this project is beyond measure. Her guidance and support in the overall economic analysis, as well as her moral support and encouragement throughout the process, made this work possible. And last, but not least, I want to thank my parents, Edward and Teresa, and my sister, Samantha, for their continued love and support.

Abstract

This paper assesses whether the enactment of the State Children's Health Insurance Program (SCHIP) in 1997, which significantly expanded child health care coverage, affected the probability of marriage for mothers in the United States. Using March CPS data from 1998-2003, I estimate the effect of a variant of state health insurance generosity towards children on the probability of the mother's marriage. When limiting my analysis to the population affected by SCHIP expansions, I find strong evidence of an "independence effect;" mothers are generally less likely (by 1 to 3%) to be married when their state of residence expands in coverage, with some mothers facing much larger percentage decreases in marriage probability. My results also reveal a disparity in incentive effects depending on the mother's situation, as some groups experience a slight increase in their probability of marriage when state health insurance coverage increases.

The Effects of SCHIP Expansions on Family Structure
Jeffrey K. Lee, Duke University
April 2006

Introduction

One of the persistent criticisms of public assistance programs in the United States is the extent to which they create incentives against labor and the formation of two-parent families. These potentially adverse consequences have led many scholars to conduct empirical research assessing the validity of these claims. Regarding the effects of public programs on family structure, scholars have found that the impact of cash benefits on marriage decisions is small and statistically insignificant (Moffitt, 1994; Hoynes, 1995; Winkler, 1995). Thus, while we would expect welfare expansions to promote marriage (as higher family income levels benefit from governmental aid, allowing for two parents to combine their incomes while still receiving aid), economic research on welfare suggests that these public financial incentives are inconsequential in the marriage market.

While the scholarship on the marital effects of US welfare programs is vast and well established, the effects of other public assistance programs have generally been neglected. Specifically, one major gap in the literature is the effects of health care programs (such as Medicaid, and the recent expansion of it via the State Children's Health Insurance Program, or SCHIP) on the likelihood of marriage. Considering that the government expenditures on Medicaid were $114 billion (excluding the elderly population) in FY2004, in comparison to $18 billion for the Temporary Assistance for Needy Families (TANF, which is commonly thought of *as* welfare) (Dahl, 2005), the minimal attention to the effects of public health insurance on marriage (and other decision-making) is puzzling. Beyond the dollar value of health programs on low-income individuals, eligibility for state health insurance may affect marriage decisions in ways that welfare programs would not. First, public health care insurance is binary (one is either covered or is not), and potential spouses may not be able to replace Medicaid/SCHIP benefits as easily as welfare benefits (due to the improbability of having employer-based health insurance offerings for low-income workers). But more importantly, low-income workers may value health care more than one might imagine, and this in turn might greatly affect their decision to enter (or leave) the marriage market.

Indeed, one previous study by Yelowitz (1998) found that, in comparison to limited coverage only for younger children, Medicaid extensions to all children in a family increased the probability of marriage by 1.7 percentage points. While his study does provide evidence that health care eligibility has a slight positive impact on the formation of two-parent families, his analysis only captures Medicaid expansions from 1989 to 1994. Since then, all states have further expanded health care coverage for children through the State Children's Health Insurance Program (SCHIP), which, established by the Balanced Budget Act of 1997, offers states high matching rates from the federal government in exchange for increased coverage for children beyond the current Medicaid boundaries (Broaddus et al, 2002). Through SCHIP, most states now cover children in families with incomes up to 200 percent of the poverty line or higher, whereas in Yelowitz's period of analysis, health insurance via Medicaid was far more limited in scope for children (by age and poverty level). New research is therefore needed in order to assess the impacts of SCHIP in the marriage market.

Furthermore, there has been much discussion on the increasing burden of health insurance on state budgets, due to enrollment increases and the overall increasing costs of health care (Madigan, 2004). Consequently, some states have begun to impose restrictions on child health care enrollment in Medicaid/SCHIP (HHN, 2004), and depending on how (and how much) these restrictions are implemented, they could very well affect marriage rates. Thus, research on the effects of recent health care expansions (specifically from SCHIP) on the probability of marriage not only fills a void in the literature, but it is also highly relevant in current policy debates. Using March CPS data from 1998-2003 (which fully covers the initial stages of SCHIP), I conduct this research, and assess the relationship between increases in state levels of coverage for children and the probability that an individual woman in the state is married. Interestingly (and counter to Yelowitz's findings), my empirical analysis suggests that increased child health care eligibility via SCHIP, when made relevant to each mother (by multiplying the level of coverage by the number of children she has), decreases the probability of marriage by an estimated 1 to 3 percent for the general population affected by the legislation change. When further limited to "more-affected" populations, the analysis reveals that the probability of marriage declined much more significantly. Part II provides a brief overview of the recent history of health insurance initiatives such as Medicaid and SCHIP. Part III outlines the various incentives that the SCHIP program provides on living arrangements, and yields predictions on its effects based on economic theory Part IV discusses the data set, while Part V presents the econometric model and the results of my analysis. Part VI concludes with the implications of my findings.

II. Recent History of Medicaid and SCHIP[1]

In past decades, the Medicaid program in the United States had been highly connected to the welfare system and the Aid to Families with Dependent Children (AFDC) program. Specifically, eligibility rules between the two programs were identical, and state income thresholds determined whether a potential recipient would be qualified for both of these programs. Thus, an individual could only qualify for Medicaid if he or she were also qualified for AFDC. However, throughout the 1980s and the early 1990s, a series of regulations severed this connection between Medicaid and AFDC. Most notably, the Omnibus Budget Reconciliation Acts of 1986-1990 allowed states to expand Medicaid coverage to children to and above the federal poverty level (FPL), thus weakening the automatic relationship between welfare eligibility rules from Medicaid rules. Whereas in 1988, no state Medicaid program covered children above the federal poverty line (with most only covering infants), by 1993 all states covered at least children under the age of 11 with family incomes under 133 percent of the FPL. Notably, in 1993 Minnesota covered all children 18 and under with family incomes at or under 275 percent of the FPL, and Vermont covered all children 17 and under within the 225 percent of the FPL.

Medicaid expansion efforts continued into the 1990s, and specifically, government assistance policy changes in 1996 and 1997 were crucial in the history of Medicaid and public medical insurance. As a result of welfare reform under the Clinton

[1] For more information on the evolution of Medicaid and SCHIP (as well as a current overview of the programs), please refer to the most recent *Green Book* (2004), a publication by the Committee on Ways and Means which can be accessed at http://waysandmeans.house.gov/Documents.asp?section=813. The Center for Medicare and Medicaid Services (CMMS) also regularly publishes a Congressional Guide on various health care programs and how they are financed. Information from the most recent guide (September 2004) was also used in the writing of this section.

administration (specifically through the Personal Responsibility and Work Opportunity Act of 1996, also known as PRWORA), a new cash welfare block called the Temporary Assistance to Needy Families (TANF) program replaced AFDC. The creation of TANF effectively severed Medicaid from government welfare programs, as a person qualified for TANF was no longer guaranteed Medicaid coverage (as was the case for AFDC recipients). Instead of linking TANF eligibility to Medicaid eligibility, government officials devised Section 1931, which stipulated that individuals who met requirements for AFDC prior to the elimination of the program were guaranteed Medicaid coverage. Furthermore, through Section 1902(r)(2) states were given more autonomy to construct their own Medicaid eligibility rules. This legislation allowed states to ignore certain types of income and assets in their calculation of the former AFDC requirements, thereby giving states the ability to extend Medicaid to other populations that would have surpassed the AFDC income thresholds under prior income calculation methods.

At the same time, the government created a new program called the State Children's Health Insurance Program (SCHIP) in 1997, in order to increase the health insurance coverage of low-income children who were not covered by Medicaid. Usually, children in the SCHIP program come from families who earn too much money to qualify for Medicaid, but an insufficient amount to be covered by private insurance. The Balanced Budget Act of 1997 called for a total federal expenditure of $39.7 billion for SCHIP over a period of ten years (1998-2007). With SCHIP, states are promised matching funds from the federal government (as with Medicaid) if they expand health coverage to all children at 200 percent of the FPL, or, if the state had a Medicaid eligibility threshold above 200 percent FPL, they are guaranteed matching funds if they increase the threshold by 50 percentage points (ex. from 225 to 275 FPL). To distribute these new healthcare benefits, states are allowed to either expand their current Medicaid program, create a new state insurance program, or create a combination of the two.

Essentially, SCHIP can be viewed as a supplement to the Medicaid program, particularly its infant and child coverage components. States implemented SCHIP beginning in February 1998, and dramatically increased their eligibility requirements for children in poor families. Tables 1, 2, and 3 (in the Appendix) show the SCHIP expansions made over the first five years of the program for eligibility requirements concerning infants (under 1), children under 6, and children between the ages of 6 and 17. Whereas in 1997 (prior to SCHIP legislation), state thresholds for infants, children under 6, and children 6-17 averaged at 177.29, 157.18, and 131.33 of the federal poverty line, respectively, state thresholds averaged 212.34, 210.97, and 211.76 for these same groups in 2002. Note that the averages across age groups converge in the latter year, reflecting the effort by the government to cover all categories of children.

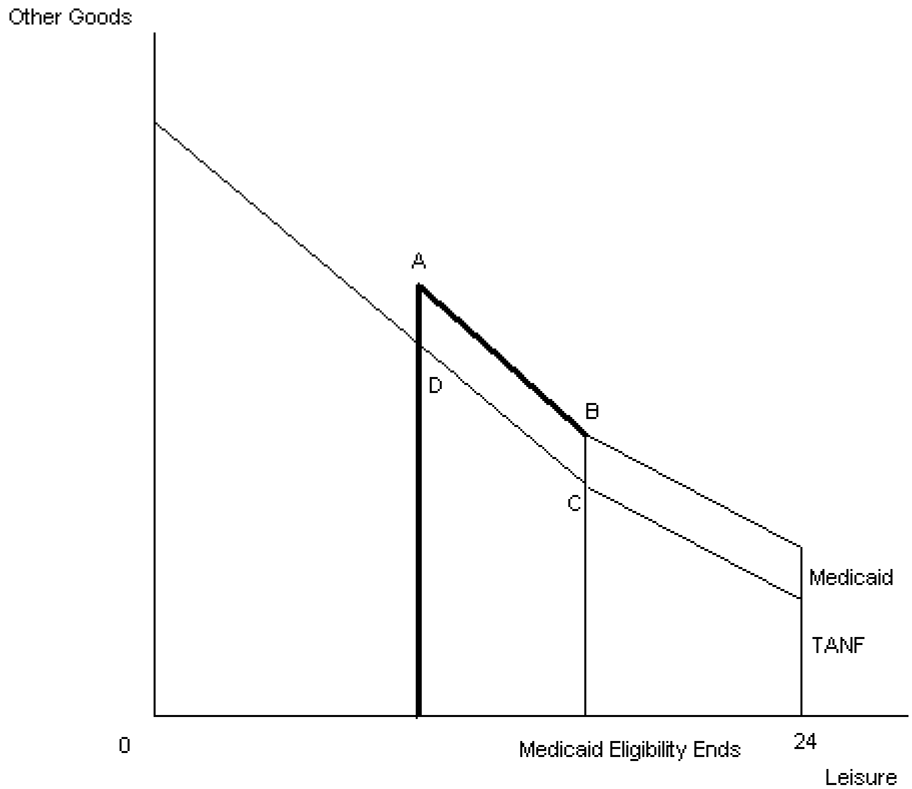
Today, children may qualify for health insurance coverage through either Medicaid or SCHIP FPL limits. Adults on the other hand have alternative avenues for access to public health insurance. As mentioned earlier, adults can quality through being eligible as part of a poor family under the previous AFDC eligibility limits for their state (set on July 16, 1996). Additionally, there are 50 population groups that are eligible for Medicaid, including pregnant women and disabled individuals. There is a also a limited amount of Medicaid for poor adults, but the poverty line thresholds are significantly lower than the FPL limits set for children under SCHIP, and have not undergone significant changes in recent times. Thus the primary incentive structure that has been altered recently and could affect the marriage market in Medicaid legislation is the large SCHIP expansions. How economic theory predicts it will do so is discussed in the next section.

III. Theoretical Effects of Medicaid/SCHIP on Marriage

Decision making with regards to the marriage market can easily be modeled by a utility maximization framework (Becker, 1981). Here, individuals assess the value/utility of marriage and will either marry, divorce, or remain single/married based on the expected utility of being married relative to the expected utility of being single. This type of model is prevalent in the welfare literature (see Gennetian and Knox 2004 or Bitler et al 2004 for recent treatments) when assessing the impact of government assistance on marriage probabilities.

Figures 1 and 2 illustrate the model in the context of Medicaid and SCHIP. The first figure refers to the budget set faced by a single mother:

FIGURE 1: Single Woman's Budget Set Before/After SCHIP Expansion

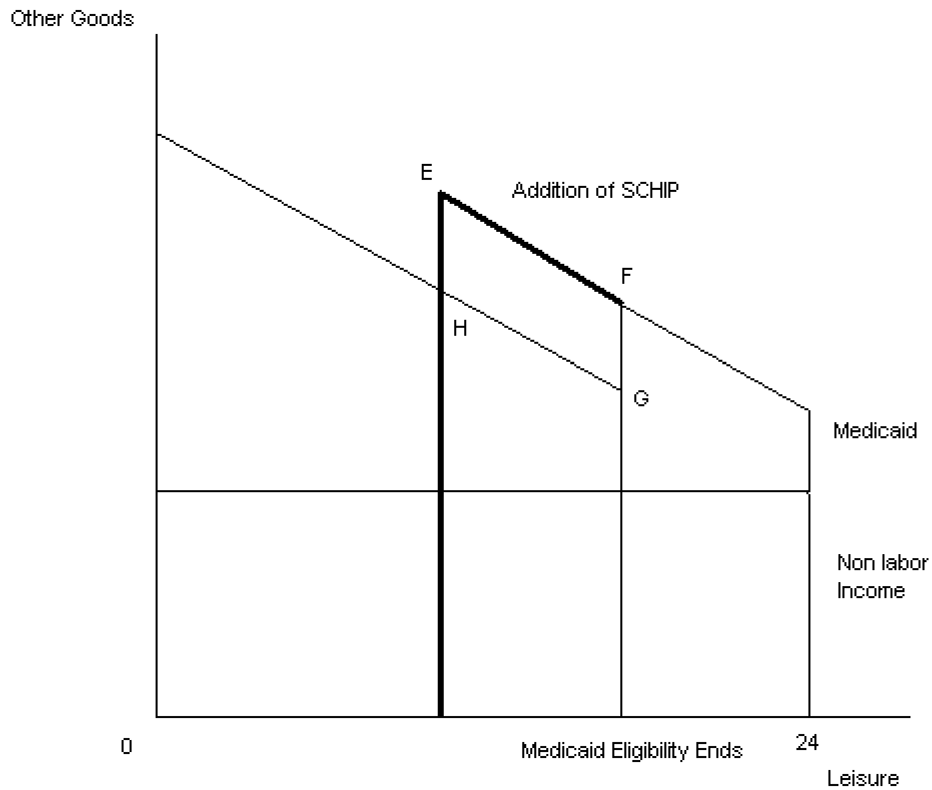


Prior to the SCHIP expansions, this single mother receives TANF payments plus Medicaid so long as she works less than a certain level (I assume that work, the opposite of leisure, translates into income, and for simplicity, that TANF and Medicaid levels end at the same FPL level). Note that in this model, TANF is treated as a lump-sum payment that decreases with a corresponding increase in work, whereas Medicaid is a constant "payment" that reduces to zero once a mother is ineligible for Medicaid. Thus, as she continues to work, her income (or more appropriately, her TANF benefits) is continually taxed away, which is the equivalent of a lower return on work (reflected in the smaller slope to the right of the eligibility line) while she still maintains the same level of Medicaid. Eventually, she works to the point where her Medicaid and TANF eligibility ends, and with no more TANF benefits to tax away, the slope of her budget line becomes steeper to reflect this loss of taxation. The bold line represents an increase in the single parent's budget line via SCHIP expansions. With this increase, the FPL threshold is higher, so the mother can work more while retaining health insurance payment. For some single mothers who were not eligible for Medicaid before, they may now face a new budget set that places them on the health insurance curve. The parallelogram ABCD represents the net change in the single mother's budget constraints via SCHIP expansions[2].

The married mother's budget set is very similar, with some exceptions. Note that the mother can leisure entirely, while receiving non labor income (via the husband, food stamps, etc). The married mother works while receiving Medicaid for the family up to a certain level (this level is likely to be lower than the single mother's level, as the married mother risks losing Medicaid due to exceeding the threshold easily with two incomes in the household). However, with SCHIP expansions, she too faces an increase in the budget set. Like the single mother, she can work more without fear of losing health care insurance. Some mothers to the left of the FG line segment will become eligible for health care insurance. The bold line represents the increase in the budget line and the new FPL threshold where it intersects the y-axis, and parallelogram EFGH represents the net budget line increases through SCHIP expansions.

[2] Even though the mother and child are not the same individual, we can assume that the mother will have to spend part of her income on caring for her children. Thus an increase in the FPL, for some mothers who were formerly not eligible, is well represented by an increase in income on the budget line.

FIGURE 2: Married Woman's Budget Set Before/After SCHIP Expansion



Because the budget sets of both single and married women expanded following SCHIP legislation, economic theory yields ambiguous predictions regarding the decision to marry. Some economists argue in favor of an "independence effect" (coined by Groeneveld, Hannan, and Tuma 1980) as the consequence of government aid such as Medicaid. That is, an increase in the budget set of a single mother may cause her to remain single instead of marrying and thus having the married mother's budget set. Similarly, a married mother, who is currently not eligible for Medicaid due to her combined income but observes the increase in the budget set for the single mother, experiences a greater incentive for divorce. On the other hand, other economists have tested the possibility of an "income effect" (Oppenheimer 1997) to SCHIP expansions; single mothers, particularly those who are afraid to marry a "wage-earner" fearing that he will place the couple over the Medicaid/welfare threshold, may find an added incentive to marry once these thresholds are higher as a result of SCHIP. Similarly, married women who benefit from SCHIP expansions may be relieved of some financial strain and therefore less likely to divorce. In one study, Bitner et al (2004) have noted that welfare reform had led to fewer divorces and fewer new marriages. In other words, the researchers found that for single mothers, the "independence" effect dominates, whereas for married mothers, the "income" effect dominates. Whether or not such findings hold for Medicaid and the recent SCHIP expansions will be discussed in the next few section.

IV. Data and Empirical Implementation

As mentioned earlier, the dataset in this study was taken from the 1998-2003 March CPS, and I will use repeated cross-sections to estimate the probability of marriage depending on the coverage generosity of the state. Please note that coverage in this paper does not reflect the amount and types of benefits that a particular mother receives (ex. dental coverage, consultation) but rather the amount of the population covered by the state, in terms of the federal poverty line. I wish to restrict my analysis to mothers between the ages of 18-55[3] with a child under the age of 19 present in the household. To create such a dataset, I have limited the observations in the survey to females who are designated as either "head/householder," "spouse," "parent," or "unmarried partner," and also belong to a household with a child under the age of 19.

[3] This restriction is consistent with Yelowitz's previous work (1998) on the effects of Medicaid; restricting the data to this age range prevents grandmothers miscoded as mothers from entering the sample, as well as teenage mothers, who would bias the results since they themselves (as children) could also be covered by SCHIP.

Next, I link each mother in the dataset to two SCHIP Federal Poverty Line (FPL) percentages relevant to her state of residence and survey year. The first is the FPL limit used to determine eligibility for a mother's children under six, and the second determines eligibility for her children under 19 (see Tables 1 and 2 in the Appendix for the FPL limits by state and year). Note that these SCHIP FPL percentages are drawn from the National Governor's Association MCH Updates, which are published every year in October. Because the CPS data that I am using reflects information in the month of March, I link each mother to the SCHIP FPL percentage that was used for eligibility in the October preceding the March CPS survey. To make this concrete, a mother from Alabama in the March 1998 survey would be assigned one FPL percentage of 133 and a second of 100 to reflect the FPL limit used by Alabama in October 1997 for children under six and children under 19, respectively.

These two FPL values – one relevant to the eligibility of a mother's children under six (which I will now call FPL_{Under6}), and one relevant to children between six and 18 (which I will now call FPL_{6To18}) – represent the state's health insurance generosity, and will serve as two of the primary explanatory variables that I am particular interested in. Through my empirical analysis, I hope to be able to determine the relationship between an increase in the percentage of the FPL covered by a state (i.e. the state's generosity) and the incidence of marriage for a mother in that state. However, an increase in the state's generosity, or percent of the FPL covered, has a different meaning for different mothers. For example, a mother with several children, whose children become eligible for SCHIP after expansions, is likely to value the expansions more than a mother with one child, and will therefore be more likely to react to FPL changes in a state. Acknowledging this distinction, I have included two additional explanatory variables of interest (both of which are interaction terms) called "FPL_{Under6}*$NumberOfKids_{Under6}$" and "FPL_{6To18}*$NumberOfKids_{6To18}$." The first variable captures the generosity of the state in terms relevant to the mother's situation, by multiplying the *percent FPL covered for children under 6* by the *number of children under 6* that a mother has. The second variable is similar, except that I multiply the *percent FPL covered for children between 6 and 18* by the *number of children between 6 and 18* that a mother has. One example is a mother in Alabama in the March 1998 survey, where the FPL percentage were 133 and 100 for children under six and children under 19, respectively. If she has two children under six, and three between the ages of 6 and 18, then her values for FPL_{Under6}*$NumberOfKids_{Under6}$ and FPL_{6To18}* $NumberOfKids_{6To18}$ would be 266 and 300, respectively.

In addition to the relevant FPL percentages, I link each mother with the relevant FPL that was used in her year. The FPL varies in magnitude from year to year, and also depends on the number of individuals in her household. I tag each observation with the FPL that each mother, based on the number of people in her household and her survey, is being evaluated on. The FPL values that are used in this analysis come from the Department of Health and Human Services, which publishes this data each February.[4] Considering that our household income data is derived from a March survey (which captures and sums the previous 12 months of income), this makes the February FPL values highly relevant when I attempt to compute whether a mother is under the relevant FPL threshold for her state of residence.

[4] Please visit http://aspe.hhs.gov/poverty/figures-fed-reg.shtml for more information on these FPL figures and to learn how they are computed each year.

In linking each mother with the Federal Poverty Line for her year of observation (relevant to the size of her household), I am able to use her household income for the year to calculate where she and her family lie, percentage-wise, on the federal poverty line (ex. 150% of the FPL, 450% of the FPL, etc.). This figure becomes highly useful later on in my analysis, when I assess whether the populations in the actual range of FPL threshold changes (generally within the 100%-300% federal poverty line) are more affected by state generosity changes than the general population. Following this line of reasoning, I also use the FPL for the mother's year of observation with her income percentage of the FPL, to assess whether her children would be eligible for SCHIP. Creating eligibility categories will be useful in assessing whether the SCHIP eligible population reacts more to a change in state generosity than the general population. To create these categories, I calculate two different indicators for eligibility – ALLELIG and PARTELIG – given the household income of each mother that is reported in the survey[5]:

- ALLELIG is an indicator variable set equal to one if the mother's household income is under the FPL cutoff for all of her children. More explicitly, ALLELIG is equal to one if her household income is within the "under 19" cutoff[6].

---

[5] The design of having multiple indicators of eligibility is borrowed from a previous investigation by Yelowitz on the effects of Medicaid eligibility on marriage (1998). However, whereas Yelowitz actually used the eligibility variables as his primary explanatory variables (to estimate whether Medicaid eligibility increases the probability of marriage), I simply use them as categories to evaluate the effects of state generosity on sub-groups in the sample. My justification for not including the eligibility variables as additional explanatory variables is that, as they are coded now, they may be endogenous to the model, because eligibility is dependent on household income, and a mother could alter her income levels to become eligible for SCHIP. Yelowitz, in fact, did not specify eligibility in the same way that I have; instead, he defined eligibility as whether a mother had any children that were within the age ranges eligible for Medicaid, which made sense in the context of the Medicaid eligibility changes that occurred from 1988-1994, but do not make sense in my analysis (all child age groups are covered in 1997 and onward).

[6] Because our observations are restricted to mothers with children, if the mother clears the lower bar of the two FPL limits (which is the "under 19" line), then all of her children will be guaranteed public health care.

- PARTELIG is an indicator variable set equal to one if the mother has a child under the age of six who is eligible for SCHIP, but also has an older child (between 6 and 18) who is not eligible for health insurance. Considering that FPL levels converge by October 1999, this variable will specifically capture the mothers in 1998 and 1999 of our data that face different FPL limits depending on whether their children are younger than six.

In creating the ALLELIG and PARTELIG categories, I wish to create a distinction between mothers whose children are all covered by SCHIP, in comparison to those mothers who have some children who are eligible for SCHIP, but others (i.e. older children) who are not because the household income exceeds the relevant FPL threshold for the state. While the ALLELIG category will helps us to answer the question of whether there is a different response to SCHIP generosity changes among the "eligible population," PARTELIG allows us to explore how mothers who experience some benefits from SCHIP but lack complete coverage respond to changes in state generosity. An analysis of the mothers in the PARTELIG category is particularly interesting, because this population experiences the greatest tension between SCHIP coverage and marriage. They are eligible to receive some health insurance coverage for their children, but risk losing this (as well as the possibility of receiving full coverage for their children) if they become married and thereby gain more household income. Essentially, the PARTELIG category allows us to explore the question of whether mothers at the cusp of receiving full SCHIP coverage are less likely to be married when the state is more generous in its health insurance coverage.

One final specification needs to be made before I can begin to analyze the data. Note that in the Appendix, some of the states for a given year do not have an FPL value indicated. This may be due either to a late introduction of SCHIP, or the failure of researchers to record the precise FPL levels used by the state in determining SCHIP/Medicaid eligibility. To deal with this missing data, I simply discard all of the observations where the state and year variables match the state and year of the missing data. This leaves me with 125,919 observations in the dataset. Table 1 presents the summary statistics of the variables used in my analysis:

Table 1
CPS Summary Statistics, 1998-2003

Variable Name	Mean	Other Comments
Mother married (%)	0.749	(0, 1), 1 = yes
Marriage rates by demographic groups		
White	0.787	104849 observations
Black	0.444	13694
Asian	0.870	5026
Other Non-White	0.604	2350
1998	0.752	18121
1999	0.748	18184
2000	0.749	12904
2001	0.758	12704
2002	0.749	31427
2003	0.746	32579
< HS Education	0.738	6580
Some HS Education	0.587	9470
HS Graduate	0.713	41618
Some College Education	0.734	37424
College Graduate	0.870	30827
18 <= age < 25	0.516	8345
25 <= age < 30	0.704	15005
30 <= age < 35	0.775	22980
35 <= age < 40	0.779	27631
40 <= age < 45	0.787	26441
45 <= age < 50	0.775	17077
50 <= age < 55	0.725	8440

FPL_{Under6}	203.064	[133. 400]
FPL_{6To18}	199.009	[100, 400]
FPL_{Under6}*$NumberOfKids_{Under6}$	270.759	[0, 2400]
FPL_{6To18}*$NumberOfKids_{6To18}$	683.274	[0, 24750]
ALLELIG	0.315	(0, 1), 1 = yes
PARTELIG	0.003	(0, 1), 1 = yes
Income Is Under FPL	0.126	(0, 1), 1 = yes
Income Between 100%-200% FPL (inclusive)	0.197	(0, 1), 1 = yes
Income Between 200%-300% FPL (excluding 200%)	0.191	(0, 1), 1 = yes
Income Over 300% FPL	0.486	(0, 1), 1 = yes
Number of Infants	0.187	[0, 5]
Age 30 and up	0.815	(0, 1), 1 = yes
Household Income	64534.23	[-19998, 987544]
Black	0.109	(0, 1), 1 = yes
White	0.833	(0, 1), 1 = yes
Asian	0.040	(0, 1), 1 = yes
Other Nonwhite	0.019	(0, 1), 1 = yes
Mother's Age	37.301	[18, 55]
< HS Education	0.052	(0, 1), 1 = yes
Some HS Education	0.075	(0, 1), 1 = yes
HS Graduate	0.331	(0, 1), 1 = yes
Some College Education	0.297	(0, 1), 1 = yes
College Graduate	0.245	(0, 1), 1 = yes
Central City	0.224	(0, 1), 1 = yes
Number of own children ages 0 to 5	0.598	[0, 6]
Number of own children ages 6 to 18	1.361	[0, 10]

Source: Author’s tabulations from March CPS, 1998-2003
Unit of observation is mother. Number of observations is 125,919.

Here, the dependent variable is marital status, with nearly three-quarters of the sample being married. By race, Asian mothers are nearly twice as likely to be married as Black mothers (87.0 percent marriage rate versus 44.4 percent), with White mothers having a slightly lower marriage rate than the former (78.7 percent). Marriage rates remain fairly constant (roughly at 75 percent) throughout the survey years, and as expected, marital rates increase until the age of 45, and marital rates are generally proportional to the amount of education a mother has (the exception is those with less than a high school education).

The remaining figures in Table 1 are independent variables to be used in the various exercises. Summarizing some of the demographics, 10.9 percent of the women in the sample are Black, 83.3 percent are White, 4.0 percent are Asian, and 1.9 percent is from other non-white racial groups. The average age of mothers is 37.3. Approximately 14 percent of the women did not finish high school, whereas over 54 percent of the women have some form of college education. Approximately 22.4 percent of the mothers live in the city, and the average number of children under age 6 and between ages 6 and 18 are approximately 0.6 and 1.4, respectively.

V. Model and Results

To estimate the effects of state SCHIP generosity on a mother's marital decision, I ran a probit model using repeated cross sections from the 1998-2003 March CPS Survey, and estimated the following equation:

$$(1)\ \text{Prob}(\text{Married}_i = 1)$$

$$= \Phi\Big(\beta_0 + \beta_1 FPL_{Under6\,j} + \beta_2 FPL_{6To18\,j} + \beta_3 FPL_{Under6\,j} \times NumberOfKids_{Under6\,i} + \beta_4\, FPL_{6To18} \times NumberOfKids_{6To18} + \beta_5 X_i + \sum_{j=2} \gamma_j S_{ij} + \sum_{k} \upsilon_j STimeTrends_j\Big)$$

Where i is an index of mothers in the dataset, j is an index of states in the dataset, $FPL_{Under6\,j}$ and $FPL_{Under6\,j}$ refer to the FPL percentage threshold (for children under and over six years of age, respectively) each state uses in assessing SCHIP eligibility in a given year (i.e. how generous each state is), and $FPL_{Under6\,j} \times NumberOfKids_{Under6}$ and

$FPL_{6To18} \times NumberOfKids_{6To18}$ is the interaction term between the FPL percentage threshold of a state (for children under and over six years of age, respectively) and the number of children that a mother has in that age group category. The latter two variables, as mentioned in previous sections, assesses the effects of state generosity when a mother has more children to care for, and can be thought of as a means of making generosity more relevant to each mother in the sample. X_i refers to the other independent variables in our analysis, and includes: *Race, Education,* and *CentralCity,* all of which are dummy variables (with *Race* referring to whether mother *i*'s race has any effect on marriage probabilities, etc.), and *Age*, Age^2, $NumberOfKids_{Under6}$ (number of children ages 0 to 5 for a mother in the sample), and $NumberOfKids_{6To18}$ (number of children ages 6 to 18 for a mother in the sample), which I argue are other exogenous individual characteristics of the mother. The second and last variable at the right end of the equation refer to state dummy variables and state time trends that I use in my model.

Table 2 presents the results for the probit model, looking at the entire dataset of mothers. None of our state generosity measures, FPL_{Under6}, $FPL_{Under6\,j}$, $FPL_{Under6j} \times NumberOfKids_{Under6}$ and $FPL_{6To18} \times NumberOfKids_{6To18}$ are statistically significant. However, many of the other variables are highly significant, and almost identical to the results found by Yelowitz (1998). Being black has a slightly smaller negative effect on the probability of marriage (-9.7 percent), while being white or Asian has a positive effect (11.1 percent and 14.0 percent, respectively). Aging by one year increases the probability of marriage by 3.8 percent (note however that the age squared term is slightly negative and significant). The data on education levels is mixed, with mothers who started but failed to complete either high school or college sharing a similar decrease in the probability of marriage (-4.3 percent and –3.5 percent, respectively). By contrast, mothers who graduated from high school (but went no further) have the smallest negative decrease in marriage probabilities (-1.3 percent), whereas mothers with less than a high school education actually have a increase in marriage probability (+3.5 percent). Central city residents face a 6.0 percent decrease in likelihood of marriage, whereas the number of kids under 6 and the number of kids between 6 and 18 seem to influence positively the probability of marriage (6.6 and 1.3 percent, respectively). Household income has a small, positive, statistically significant effect on the probability of marriage. The small economic significance of the coefficient makes sense when the unit of change (one dollar) is considered.

Table 2
Basic Results
Probit Model for the Effects of State Generosity on Marriage

Independent Variable	Dependent Variable = married
FPL_{Under6}*$NumberOfKids_{Under6}$	**0.00004**
	(0.0000)
FPL_{6To18}*$NumberOfKids_{6To18}$	**0.00001**
	(0.0000)
FPL_{Under6}	**0.00008**
	(0.0001)
FPL_{6To18}	**-0.00008**
	(0.0001)
Income	**0.00000371*** **
	(0.0000)
Black	**-0.09661*** **
	(0.0101)
White	**0.11138*** **
	(0.0093)
Asian	**0.13954*** **
	(0.0046)
Age	**0.03753*** **
	(0.0012)
Age Squared	**-0.00048*** **
	(0.0000)
< HS Education	**0.03538*** **

	(0.0059)
Some High School Education	**-0.04255*****
	(0.0065)
High School Graduate	**-0.01290*****
	(0.0042)
Some College Education	**-0.03526*****
	(0.0040)
Central City	**-0.05982*****
	(0.0032)
Number of Children Ages 0 to 5	**0.06590*****
	(0.0076)
Number of Children Ages 6 to 18	**0.01339*****
	(0.0044)
Pseudo R^2	0.1962

Source: Author's tabulations from March CPS, 1998-2003
Coefficients (in bold) are marginal effects for each variable
Note: Robust Standard Errors are in parenthesis
State effects and State Time Trends have been absorbed
* statistically significant at the 10% level
** statistically significant at the 5% level
*** statistically significant at the 1% level

Thus far, our findings from Table 2 do not suggest that there are any effects of state health care on the probability of marriage. However, given that we are looking at the entire dataset of mothers in this model, the non-significant results on the generosity variables might make sense. Intuitively, the data captures mothers of a wide range of household incomes; according to Table 1, nearly 50% of the mothers in the sample have a household income over 300% of the federal poverty line. Most of these mothers' children would not be eligible for public health insurance coverage, and many of them probably do not pay attention to state health insurance coverage increases, let alone allow them to influence their marriage decision-making. Perhaps if we restrict our analysis to poorer mothers, who are in or around the range of SCHIP coverage and might actually be affected by an increase in state generosity, we might some effect of state generosity on the probability of marriage.

Table 3 provides the results of the probit model when restricted to populations potentially affected by changes in state health care generosity. Specification 1 limits the analysis to mothers under the federal poverty line for their year, while Specifications 2 and 3 looks at mothers whose household incomes place them between 100-200% (inclusive) and 200-300% (excluding income = 200% FPL) of the federal poverty line for their year. Note that Specifications 2 and 3 are of particular interest; most of the state insurance thresholds changes fall in these two ranges, and these mothers should be considered most likely to be affected by changes and react to them (ex. by altering family structure decisions). Specification 4 looks at mothers over 300% of the FPL, a group which we generally expect to be unaffected by generosity increases. Finally, Specification 5 and 6 restrict the analysis to ALLELIG and PARTELIG categories, which as mentioned in Part IV, reflects the mothers who either have all of their children covered by SCHIP (on the basis of their household incomes) or some but not all of their children covered, respectively.

Of particular interest is the PARTELIG category, because it represents the mothers who either recently became partially eligible for SCHIP or are on the cusp of becoming fully eligible for full SCHIP coverage for her children. Their decision to be in a marriage most greatly affects their children's health insurance status, because additional income from a husband could swing them out of any health insurance coverage, or prevent their children from being fully covered. If these mothers see their situation from this perspective, then we might conclude that an "independence effect" is at play – i.e., that mothers are remaining or becoming single to gain public health insurance benefits. Alternatively, the mothers who are partially eligible may be mothers who see the additional aid as stress relief; in this case, the health insurance expansions have an "income effect," helping their current marriage to last, or providing them with enough public support so that they won't lose full child health care coverage with an increase in income from a husband. In sum, while the presence of SCHIP benefits could yield either an "income" or "independence" effect, the effect should be greatest when being married (which increases household income) most directly affects the SCHIP status of a mother's children. The 100%-200% FPL, and the 200%-300% FPL categories capture this population to some extent, but the most precise measure of a group where marriage and health insurance coverage are potentially at odds lies in the PARTELIG category.

Table 3
Effects of Generosity on Marriage for Affected Populations

	Dependent Variable = married					
	(1)	(2)	(3)	(4)	(5)	(6)
Independent Variable	Under FPL	Between 100%-200% FPL	Between 200%-300% FPL[7]	Over 300% FPL	ALLELIG	PARTELIG
FPL_{Under6} * $NumberOfKids_{Under6}$	**0.00004**	**-0.00031*****	**-0.00020***	**-0.00001**	**0.00015***	**-0.00328****
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0016)
FPL_{6To18} * $NumberOfKids_{6To18}$	**-0.00015****	**-0.00009**	**-0.00006**	**0.00001**	**-0.00008**	**-0.0070*****
	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0021)
FPL_{Under6}	**0.00002**	**0.0001204**	**-0.00015**	**0.00014**	**0.00001**	**0.0005**
	(0.0003)	(0.0003)	(0.0002)	(0.0001)	(0.0002)	(0.0061)
FPL_{6To18}	**0.00027**	**-0.0000518**	**0.00034***	**-0.00012**	**0.00000**	**0.0020**
	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0063)
Income	**0.0000*****	**0.00003*****	**0.00002*****	**0.00000*****	**0.00002*****	**0.0001*****
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Black	**-0.1741*****	**-0.10856*****	**-0.13430*****	**-0.04406*****	**-0.16359*****	**-0.7067*****
	(0.0239)	(0.0242)	(0.0278)	(0.0132)	(0.0182)	(0.1937)
White	**0.1370*****	**0.14711*****	**0.05516****	**0.05269*****	**0.13474*****	**-0.1233**
	(0.0227)	(0.0221)	(0.0230)	(0.0124)	(0.0167)	(0.1388)
Asian	**0.3373*****	**0.23397*****	**0.13712*****	**0.06496*****	**0.27767*****	**-0.61760***
	(0.0299)	(0.0157)	(0.0145)	(0.0050)	(0.0152)	(0.2769)

[7] Note that this category excludes those whose income is at exactly 200% of the FPL, but includes those with incomes at exactly 300% of the FPL. By contrast, the "Between 100%-200% FPL" specification is inclusive on both ends.

Age	0.0306***	0.03894***	0.04808***	0.02842***	0.04106***	0.0150
	(0.0038)	(0.0032)	(0.0030)	(0.0013)	(0.0026)	(0.0263)
Age Squared	-0.0004***	-0.00056***	-0.00065***	-0.00035***	-0.00056***	-0.0004
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0004)
< HS Education	-0.0941***	0.03390**	0.05991***	0.00304	0.02318*	-0.4900***
	(0.0213)	(0.0165)	(0.0143)	(0.0112)	(0.0139)	(0.1629)
Some High School Edu.	-0.2061***	-0.06681***	0.02164	-0.01818**	-0.10080***	-0.4609***
	(0.0187)	(0.0161)	(0.0128)	(0.0086)	(0.0131)	(0.1596)
High School Graduate	-0.1945***	-0.06849***	0.01237	0.00010	-0.09420***	-0.32074**
	(0.0194)	(0.0132)	(0.0082)	(0.0031)	(0.0116)	(0.1315)
Some College Education	-0.2294***	-0.14199***	-0.01530*	-0.00846***	-0.16237***	-0.35558**
	(0.0179)	(0.0140)	(0.0084)	(0.0029)	(0.0120)	(0.1627)
Central City	-0.0495***	-0.06482***	-0.06351***	-0.04300***	-0.05730***	-0.0531
	(0.0101)	(0.0084)	(0.0079)	(0.0036)	(0.0068)	(0.0629)
Number of Children Ages 0 to 5	0.04596**	0.09176***	0.04482*	0.07774***	0.04374**	0.2263
	(0.0220)	(0.0228)	(0.0240)	(0.0109)	(0.0172)	(0.2275)
Number of Children Ages 6 to 18	0.03261**	-0.02214*	-0.05295***	0.02470***	0.02337**	0.6562***
	(0.0131)	(0.0131)	(0.0132)	(0.0065)	(0.0104)	(0.2184)
Average $\text{NumberOfKids}_{\text{Under6}}$	0.839	0.724	0.604	0.482	0.755	1.373
Average $\text{NumberOfKids}_{\text{6To18}}$	1.583	1.455	1.400	1.249	1.509	1.739
Number of Observations	15942	24756	24061	61660	39617	344
Pseudo R^2	0.1625	0.1815	0.1837	0.1085	0.1848	0.3821

Source: Author's tabulations from March CPS, 1998-2003
Note: Robust Standard Errors are in parenthesis
Coefficients (in bold) are marginal effects for each variable
State effects and State Time Trends have been absorbed
* statistically significant at the 10% level
** statistically significant at the 5% level
*** statistically significant at the 1% level

Interestingly, looking at Specifications 1-6 in Table 3, some of these generosity variables (specifically the interaction terms) are now statistically significant. While the values for the interaction term coefficients appear to be small in economic significance, it is important to note that the coefficients represent the change in the probability of marriage due to a 1-unit increase in the interaction term. This interpretation is relatively meaningless, because what we are interested in is the change in marriage probabilities due to an increase in the state's generosity of health insurance coverage, not a 1-unit increase in an interaction term. To interpret these interaction terms in a meaningful way, I estimate the number of units the interaction term would change given a typical increase in a state's FPL threshold from1998-2003. The typical increase in FPL_{Under6} and FPL_{6To18} that I use for this calculation is approximately 50.431 and 81.667 percentage points, respectively, which is the average increase in the level of SCHIP coverage by each state over the six year period I study (derived from Tables 1 and 2 in the Appendix). I then multiply these values (50.431 and 81.667) by the average number of children under 6 and between 6 and 18 (per household) for each specification (reported at the bottom of Table 3), respectively, to get the typical increase in the interaction term per mother due to a typical increase in FPL thresholds.

Using this estimated change in the interaction term, I am able to estimate the approximate change in the probability of marriage due to an increase in FPL coverage from SCHIP legislation. The results of this adjustment, limited to the interaction terms in Table 3, are reported in Table 4. For the population under the federal poverty line, a typical increase in the FPL threshold for 6 to 18 year olds led to a 1.98 percent decrease in the probability of marriage. Similarly, for the population between 100%-200% of the FPL, I observe a 1.13 percent decrease in the probability of marriage with a typical increase in the FPL threshold for children under 6. Between 200%-300% of the FPL, an average increase in the FPL threshold for children under 6 leads to a 0.61 percent decrease in the probability of marriage, although this result is only statistically significant at the 10% level. For the population over 300% of the FPL, there is no statistically significant effect of a typical increase in coverage on the probability of marriage, a result that is expected, since wealthier populations are probably less interested and less affected by public health insurance coverage increases, as mentioned earlier.

Table 4
Effects of Average Increase in Generosity on Marriage for Affected Populations

	Dependent Variable = married					
	(1)	(2)	(3)	(4)	(5)	(6)
Independent Variable	Under FPL	Between 100%-200% FPL	Between 200%-300% FPL	Over 300% FPL	ALLELIG	PARTELIG
FPL_{Under6}*$NumberOfKids_{Under6}$	**0.00186**	**-0.01127***	**-0.00605***	**-0.00019**	**0.00564***	**-0.22706****
FPL_{6To18}*$NumberOfKids_{6To18}$	**-0.01977****	**-0.01069**	**-0.00633**	**0.00057**	**-0.00928**	**-0.99535*****
Number of Observations	15942	24756	24061	61660	39617	344
Pseudo R^2	0.1625	0.1815	0.1837	0.1085	0.1848	0.3821

The ALLELIG category in Table 4 provides an interesting exception to the general rule we have witnessed thus far, that an increase in state generosity leads to a decrease in the probability of marriage for mothers in poorer populations. It appears that for the population of mothers where all of their children are eligible for SCHIP, a typical increase in FPL coverage is associated with a 0.5 percent *increase* in the probability of marriage, though this result is only statistically significant at the 10% level. One explanation for this slight increase in marriage probabilities for the ALLELIG population is that unlike the other specifications (1-4 and 6), this category includes the poorest mothers in my dataset, who are almost assured of health insurance coverage due to their low household income, and face a smaller incentive to remain single or divorce (an ,increase in income through marriage will not be as likely to knock them out of coverage). However, specification 1 also contains the poorest mothers, and does not exhibit a statistically significant positive effect of generosity increase on marriage, which causes the result in specification 5 to be slightly puzzling. While I cannot conclude on why there is a discrepancy between specification 1 and 5, one should note at the very least the possibility that some groups (specifications 1, 2 and 3 thus far) see health insurance coverage as an “independence effect,” whereas others (specification 5) might see it as an “income effect” in favor of marriage.

Finally, whereas the ALLELIG category provides some evidence that an “income effect” exists for SCHIP expansions, the PARTELIG category supports the “independence effect” that we see in specifications 1, 2, and 3, although with much bolder results. For children under 6 in this category, a typical increase in the FPL threshold leads to a 22.71 percent decrease in the probability of marriage that is significant at the 5% level. And for children between 6 and 18 in the PARTELIG category, a typical increase in the relevant FPL threshold almost guarantees that the mother will not be married (a 99.54% decrease in the probability of marriage). This stronger result for the changes to the older group’s threshold (relative to the younger group) is expected, based on the inherent characteristics of the PARTELIG population. Mothers in the PARTELIG group have their children under the age of 6 covered by SCHIP, but on the other hand, their children 6 and older are not eligible for coverage. The FPL threshold for younger children would matter to these mothers, because if they exceed the thresholds they will lose all SCHIP coverage. However, the threshold that is more likely to garner their attention is the threshold for older children, which, if they manage to fall within it, will allow all of their children to receive public health insurance. Therefore, the possibility of gaining full coverage may serve as a major deterrent to marriage for these mothers. As predicted by the interaction term, given a certain FPL threshold level for older children, if the mother has more children, then full health insurance coverage will matter to her even more. While it appears through the

PARTELIG population that the "independence effect" is loud and present, caution must be placed on the results of this specification. It is more important to note the odd behavior of specification 6, as seen in Table 3. Some of the other typical explanatory variables (ex. race, education, etc.) appear to have quite different effects in this specification relative to other specifications in the table, suggesting that this sub-group may be very abnormal and unrepresentative. Furthermore, the small sample size in the PARTELIG category (N = 344) relative to the other specifications may cause results to be less accurate.

Overall, is an "independence effect" for SCHIP coverage truly dominant among the affected populations, relative to the income effect? In an attempt to shed more light on this question, I provide a variety of alternative exercises to reveal more about the effects of SCHIP eligibility on marriage probabilities in different populations. My first exercise to test the "independence effect" involves re-running the probit model, but this time, restricting observations to the top nine TANF (welfare) giving states, as well as the bottom nine benefit giving states[8]. The logic behind these restrictions is that women in the top nine states should be subject to a minimal "independence effect;" mothers in these states have relatively more money (due to increase welfare), and are therefore less likely to be affected by an increase in Medicaid/SCHIP eligibility. In other words, mothers in states that give higher welfare benefits are relatively more independent (because they have more money), and are less likely to remain single or divorce when provided with

[8] The top nine states were computed by averaging the monthly benefit levels for a family of three in all fifth states from July 1995 to June 2002, and they were, in order of first to ninth: Alaska, Wisconsin, Massachusetts, Vermont, California, New Hampshire, New York, Hawaii and Rhode Island. The bottom nine states, in comparison, from 42nd to dead last, were: North Carolina, Kentucky, Louisiana, Arkansas, South Carolina, Texas, Tennessee, Mississippi, and Alabama. The data used can be found online at: http://www.ripolicyanalysis.org/TANF03ARCh12Tab2.xls.

increased public health care coverage (or the opportunity of gaining it). Likewise, in the bottom nine states, an increase in SCHIP eligibility will make the mother more independent, and thus less likely to be married.

After re-running the probit model for high and low welfare states, I find some evidence of a lesser "independence effect" in the top nine states, though the differences between the top nine states and the bottom nine states are not tremendous. Table 5 compares a probit specification featuring the top nine TANF states (specification 1) with one featuring the bottom nine TANF states (specification 2). While there are some differences between the explanatory variables (most notably, the difference in being Black) in Specification 1 and 2, the marginal effects displayed in Table 5 look very similar overall. The generosity variables, at the top of the table, are not statistically significant in either model (similar to the result in Table 2); therefore, we have no means of comparing the two populations and how they react to increase SCHIP coverage in this table. Just as I did in the previous analysis, I will now try to break down this analysis into poorer sub-groups of the dataset, to see if at this level we can observe a difference between the top nine TANF states and the bottom nine TANF states. Table 6 provides specifications comparing the top and bottom nine welfare states, for the mothers below the FPL, between 100-200% of the FPL, and between 200-300% of the FPL, whereas Table 7 extends the top-bottom welfare state comparison to mothers over 300% of the FPL, mothers who are in the ALLELIG category, and mothers who are in the PARTELIG category. Table 8 presents the adjusted coefficient values relevant to typical state generosity increases (in a fashion similar to Table 4 for the earlier analysis).

Table 5
Effects of Generosity on Top and Bottom Nine TANF States (General Group)

	(1)	(2)
	Dependent Variable = married	
Independent Variable	Top Nine TANF	Bottom Nine TANF
FPL_{Under6}*$NumberOfKids_{Under6}$	**0.00010**	**-0.00003**
	(0.0001)	(0.0001)
FPL_{6To18}*$NumberOfKids_{6To18}$	**0.00003**	**-0.00003**
	(0.0000)	(0.0001)
FPL_{Under6}	**0.00001**	**0.00012**
	(0.0003)	(0.0001)
FPL_{6To18}	**-0.00011**	**0.00000**
	(0.0003)	(0.0002)
Income	**0.00000*** **	**0.00000*** **
	(0.0000)	(0.0000)
Black	**-0.04593*** **	**-0.13611*** **
	(0.0187)	(0.0310)
White	**0.12633*** **	**0.09083*** **
	(0.0182)	(0.0283)
Asian	**0.15879*** **	**0.13264*** **
	(0.0085)	(0.0168)
Age	**0.04465*** **	**0.02773*** **
	(0.0024)	(0.0029)
Age Squared	**-0.00058*** **	**-0.00037*** **
	(0.0000)	(0.0000)
< HS Education	**0.02224***	**0.01101**
	(0.0114)	(0.0166)
Some High School Education	**-0.06275*** **	**-0.03582** **
	(0.0133)	(0.0163)
High School Graduate	**-0.01271**	**-0.02551** **
	(0.0083)	(0.0122)
Some College Education	**-0.04916*** **	**-0.04150*** **
	(0.0082)	(0.0110)
Central City	**-0.04645*** **	**-0.06073*** **
	(0.0057)	(0.0080)
Number of Children Ages 0 to 5	**0.04501** **	**0.06524*** **
	(0.0184)	(0.0203)
Number of Children Ages 6 to 18	**0.00233**	**0.02009***
	(0.0105)	(0.0104)
Number of Observations	31651	20578
Pseudo R^2	0.1735	0.2043

Source: Author's tabulations from March CPS, 1998-2003
Note: Robust Standard Errors are in parenthesis
Coefficients (in bold) are marginal effects for each variable
State effects and State Time Trends have been absorbed
* statistically significant at the 10% level
** statistically significant at the 5% level
*** statistically significant at the 1% level

Table 6
Effects of Generosity on Top and Bottom Nine TANF States Lowest Income Levels)

	(1)		(2)		(3)	
	Dependent Variable = married					
	Income Under FPL		Income Between 100-200% FPL		Income 200-300% FPL	
Independent Variable	Top Nine TANF	Bottom Nine TANF	Top Nine TANF	Bottom Nine TANF	Top Nine TANF	Bottom Nine TANF
FPL_{Under6} * $NumberOfKids_{Under6}$	**0.00056*** **	**0.00015**	**-0.00040***	**-0.00044***	**0.00000**	**0.00010**
	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
FPL_{6To18} * $NumberOfKids_{6To18}$	**0.00006**	**-0.00021**	**-0.00016**	**-0.00027** **	**-0.00017**	**0.00019**
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0002)
FPL_{Under6}	**-0.00007**	**-0.00064**	**-0.00059**	**0.00035**	**-0.00062**	**-0.00004**
	(0.0011)	(0.0005)	(0.0010)	(0.0004)	(0.0008)	(0.0003)
FPL_{6To18}	**-0.00042**	**0.00068**	**0.00052**	**-0.00006**	**0.00098**	**-0.00007**
	(0.0009)	(0.0005)	(0.0008)	(0.0004)	(0.0007)	(0.0004)
Income	**0.00002*** **	**0.00003*** **	**0.00002*** **	**0.00003*** **	**0.00002*** **	**0.00002*** **
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Black	**-0.02617**	**-0.06619**	**0.01596**	**-0.16773** **	**-0.06476**	**-0.14343** **
	(0.0598)	(0.0824)	(0.0451)	(0.0703)	(0.0485)	(0.0782)
White	**0.19956*** **	**0.29505*** **	**0.21264*** **	**0.09909**	**0.09854** **	**0.05476**
	(0.0500)	(0.0712)	(0.0441)	(0.0675)	(0.0439)	(0.0683)
Asian	**0.39984*** **	**0.38604*** **	**0.25399*** **	**0.27205*** **	**0.16867*** **	**0.09983**
	(0.0470)	(0.0790)	(0.0260)	(0.0366)	(0.0233)	(0.0579)
Age	**0.03974*** **	**0.02395*** **	**0.04850*** **	**0.01211***	**0.06734*** **	**0.02549*** **
	(0.0075)	(0.0086)	(0.0062)	(0.0071)	(0.0063)	(0.0072)
Age Squared	**-0.00053*** **	**-0.00032*** **	**-0.00069*** **	**-0.00022** **	**-0.00090*** **	**-0.00037*** **
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
< HS Education	**-0.14954*** **	**-0.15688*** **	**-0.03299**	**0.01189**	**0.08214*** **	**0.04964**
	(0.0402)	(0.0513)	(0.0313)	(0.0402)	(0.0237)	(0.0338)
Some High School Education	**-0.25831*** **	**-0.20170*** **	**-0.10972*** **	**-0.04396**	**0.01548**	**0.00623**
	(0.0356)	(0.0493)	(0.0324)	(0.0367)	(0.0262)	(0.0315)
High School Graduate	**-0.21106*** **	**-0.23222*** **	**-0.10511*** **	**-0.05823***	**0.03166***	**0.02598**
	(0.0381)	(0.0500)	(0.0271)	(0.0320)	(0.0171)	(0.0200)
Some College Education	**-0.23384*** **	**-0.26854*** **	**-0.18204*** **	**-0.11938*** **	**-0.01698**	**-0.02435**
	(0.0363)	(0.0439)	(0.0289)	(0.0342)	(0.0178)	(0.0208)
Central City	**-0.01576**	**-0.07060*** **	**-0.02493***	**-0.05563*** **	**-0.03338** **	**-0.09785*** **
	(0.0175)	(0.0231)	(0.0142)	(0.0195)	(0.0142)	(0.0197)
Number of Children Ages 0 to 5	**-0.08762***	**0.01774**	**0.12327** **	**0.09513***	**0.00431**	**-0.04098**
	(0.0483)	(0.0501)	(0.0540)	(0.0514)	(0.0648)	(0.0640)

Number of Children Ages 6 to 18	**-0.02977**	**0.04731**	**0.00647**	**0.01461**	**-0.02124**	**-0.09964*****
	(0.0256)	(0.0301)	(0.0343)	(0.0262)	(0.0341)	(0.0309)
Average $NumberOfKids_{Under6}$	0.823	0.863	0.711	0.706	0.608	0.571
Average $NumberOfKids_{6To18}$	1.700	1.496	1.507	1.378	1.421	1.310
Number of Observations	4458	3301	6262	4695	5603	4037
Pseudo R^2	0.1534	0.1965	0.1412	0.1766	0.1593	0.189

Source: Author's tabulations from March CPS, 1998-2003
Note: Robust Standard Errors are in parenthesis
Coefficients (in bold) are marginal effects for each variable
State effects and State Time Trends have been absorbed
* statistically significant at the 10% level
** statistically significant at the 5% level
*** statistically significant at the 1% level

Table 7

Effects of Generosity on Top and Bottom Nine TANF States (Over 300% FPL, ALLELIG, PARTELIG)

	(4)		(5)		(6)	
	Dependent Variable = married					
	Income Over 300% FPL		ALLELIG		PARTELIG	
Independent Variable	Top Nine TANF	Bottom Nine TANF	Top Nine TANF	Bottom Nine TANF	Top Nine TANF	Bottom Nine TANF
FPL_{Under6} * $NumberOfKids_{Under6}$	**-0.00010**	**0.00000**	**0.00036****	**0.00025**	**-0.00304**	**-0.00135****
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0022)	(0.0005)
FPL_{6To18} * $NumberOfKids_{6To18}$	**-0.00004**	**0.00001**	**0.00005**	**-0.00015**	**-0.00327****	**-0.00101***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0017)	(0.0005)
FPL_{Under6}	**0.00035**	**0.00017**	**-0.00071**	**0.00003**	**0.00934**	n/a
	(0.0004)	(0.0001)	(0.0008)	(0.0003)	(0.0056)	n/a
FPL_{6To18}	**-0.00025**	**-0.00015**	**0.00014**	**-0.00029**	**-0.00289**	n/a
	(0.0003)	(0.0002)	(0.0007)	(0.0004)	(0.0045)	n/a
Income	**0.00000*****	**0.00000*****	**0.00001*****	**0.00002*****	**0.00001**	**0.00006*****
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Black	**-0.04944****	**-0.04429**	**-0.04107**	**-0.14159*****	n/a	n/a
	(0.0251)	(0.0391)	(0.0364)	(0.0549)	n/a	n/a
White	**0.05029*****	**0.02775**	**0.17493*****	**0.19059*****	**0.55076***	**0.73411*****
	(0.0215)	(0.0345)	(0.0331)	(0.0529)	(0.3065)	(0.1467)
Asian	**0.07666*****	**0.04814***	**0.28234*****	**0.33747*****	**0.10758**	**-0.14406**
	(0.0095)	(0.0187)	(0.0236)	(0.0379)	(0.0808)	(0.2642)
Age	**0.03187*****	**0.02746*****	**0.05043*****	**0.02139*****	**0.01296**	**-0.00636**
	(0.0028)	(0.0034)	(0.0047)	(0.0060)	(0.0469)	(0.0241)
Age Squared	**-0.00039*****	**-0.00034*****	**-0.00069*****	**-0.00031*****	**-0.00023**	**-0.00003**
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0006)	(0.0003)
< HS Education	**0.00690**	**0.01698**	**0.01108**	**-0.04052**	**-0.19227**	**-0.83612*****
	(0.0193)	(0.0283)	(0.0228)	(0.0382)	(0.2115)	(0.1850)
Some High School Education	**-0.05059*****	**0.00241**	**-0.10133*****	**-0.10372*****	**-0.27221**	**-0.65296****

	(0.0199)	(0.0170)	(0.0232)	(0.0352)	(0.2435)	(0.3084)
High School Graduate	**-0.00090**	**-0.00983**	**-0.07088*** **	**-0.13733*** **	**-0.07540**	**-0.51594*** **
	(0.0067)	(0.0083)	(0.0204)	(0.0329)	(0.1541)	(0.1975)
Some College Education	**-0.01939*** **	**0.00167**	**-0.14993*** **	**-0.19818*** **	**-0.43265**	**-0.76191*** **
	(0.0063)	(0.0073)	(0.0214)	(0.0337)	(0.3092)	(0.2371)
Central City	**-0.03921*** **	**-0.04884*** **	**-0.02501** **	**-0.07159*** **	**-0.06952**	**-0.03261**
	(0.0064)	(0.0088)	(0.0109)	(0.0166)	(0.0933)	(0.0821)
Number of Children Ages 0 to 5	**0.09882*** **	**0.06560** **	**-0.02459**	**0.00930**	**0.44940**	n/a
	(0.0291)	(0.0295)	(0.0363)	(0.0401)	(0.3552)	n/a
Number of Children Ages 6 to 18	**0.03641** **	**0.01324**	**-0.01781**	**0.04239* **	**0.40048** **	n/a
	(0.0172)	(0.0151)	(0.0212)	(0.0238)	(0.1743)	n/a
Average $NumberOfKids_{Under6}$	0.503	0.467	0.732	0.774	1.304	1.292
Average $NumberOfKids_{6To18}$	1.242	1.190	1.569	1.421	1.810	1.726
Number of Observations	15328	8545	12066	7024	74	113
Pseudo R^2	0.1084	0.098	0.1561	0.197	0.2352	0.5358

Source: Author's tabulations from March CPS, 1998-2003
Note: Robust Standard Errors are in parenthesis; several parameters were not estimable (denoted n/a)
Coefficients (in bold) are marginal effects for each variable
State effects and State Time Trends have been absorbed
* statistically significant at the 10% level
** statistically significant at the 5% level
*** statistically significant at the 1% level

Looking at Table 8, one can see that many of the generosity variables (the interaction terms) are statistically significant, allowing us to compare, to some extent, the effects of typical increase in health insurance coverage generosity between top and bottom welfare states. First, note that for mothers under the FPL and ALLELIG mothers, the effect of an increase in FPL threshold for children under 6 is *positive* for marriage probabilities, not only supporting the notion that high welfare states face less of an independence effect, but that they also appear to face an income effect in some populations, a finding not observed in any of the bottom nine TANF categories. Second, note the direct comparison at the 100-200% FPL between the top and bottom welfare states; although the results are significant at the 10% level, they suggest that the top welfare states have a slightly lower decrease in the probability of marriage given a typical increase in the generosity of the state[9], again supporting the idea of a decreased "independence effect" for higher welfare states. Furthermore, the negative coefficient for the bottom nine TANF states in the 100-200% FPL group, compared to no statistically significant evidence for the top welfare states in the same category, reinforces this idea of a stronger "independence effect" in lower welfare states. The exception to this general picture is in the PARTELIG category, where for older children, an increase in the FPL threshold appears to have a greater "independence effect" for the top nine TANF states. However, the smaller negative coefficient for the bottom nine states is only significant at the 10% level. Further, the substantial difference between the PARTELIG probit results (for many of the explanatory variables – see Table 7) and the rest of the specifications, in combination with the smaller sample size of the PARTELIG category, calls into question the reliability of the estimates in this sub-group.

In sum, my analysis suggests that an increase in SCHIP, when made relevant to each mother based on the number of children she has, generally is associated with a decrease in the probability of marriage for poorer populations and an "independence effect." This relationship between independence and SCHIP generosity is further revealed through an analysis of high and low welfare states, which provide us with a scenario where independence is highly and lowly established, allowing SCHIP to have a low and high effect on independence, respectively. For some populations, however, SCHIP appears to be a source of income relief that encourages marriage – this "income effect" seems to exist among the poorest populations in my dataset. Perhaps surprisingly,

[9] Note that the difference in number of children per age group is not controlled for in the results found in Table 8. However, the direct comparison made between the top and bottom nine TANF states in the 100-200% FPL group seems highly valid given the difference in average number of children under 6 per mother is very small.

SCHIP health insurance coverage, particularly in “affected populations” appear to provide a complex range of incentives and disincentives to mothers that ultimately do play a role – be it “independence” or “income” supporting, in her marriage decision making.

Table 8

Effects of Average Increase in Generosity on Marriage for Affected Populations (Top vs. Bottom Nine TANF states)

	Dependent Variable = married											
	Income Under FPL		Income Between 100-200% FPL		Income 200-300% FPL		Income Over 300% FPL		ALLELIG		PARTELIG	
Independent Variable	Top 9 TANF	Bottom 9 TANF	Top 9 TANF	Bottom 9 TANF	Top 9 TANF	Bottom 9 TANF	Top 9 TANF	Bottom 9 TANF	Top 9 TANF	Bottom 9 TANF	Top 9 TANF	Bottom 9 TANF
FPL_{Under6}*$NumberOfKids_{Under6}$	**0.02327*****	**0.00668**	**-0.01440***	**-0.01584***	**0.00009**	**0.00291**	**-0.00249**	**0.00002**	**0.01318****	**0.00959**	**-0.19974**	**-0.08799****
FPL_{6To18}*$NumberOfKids_{6To18}$	**0.00819**	**-0.02551**	**-0.02010**	**-0.03039****	**-0.01994**	**0.02081**	**-0.00400**	**0.00084**	**0.00688**	**-0.01785**	**-0.48330****	**-0.14306***
Number of Observations	4458	3301	6262	4695	5603	4037	15328	8545	12066	7024	74	113
Pseudo R^2	0.1534	0.1965	0.1412	0.1766	0.1593	0.189	0.1084	0.098	0.1561	0.197	0.2352	0.5358

VI. Discussion and Conclusion

Overall, the results of this study suggest that a proxy for the value of an increase in the SCHIP coverage of a state from a mother's perspective (FPL level coverage interacted with the number of young and old children a mother has) has led to a decrease in the probability of marriage, generally ranging from approximately 1 to 3 percent depending on which group I observe in the model. The more relevant health care coverage is to a mother (as seen through an increase in the number of children she has), the more important the state's coverage level is to her {and the more she will decrease her probability of marriage). Based on my empirical analysis, there is some evidence that the "independence effect" is at play, and that mothers that are more likely to be affected by increases in coverage levels tend to have a decrease in the probability of married, with the most pronounced effect coming from mothers whose children were only partially covered by SCHIP in the dataset. Centering around the federal poverty levels where SCHIP expanded, the results in my study suggest that a direct tension exists between marriage and health insurance, and that with greater potential to receive health insurance, a mother is likely to sacrifice marriage for her children's SCHIP coverage. Interestingly, there is also some evidence suggesting that while some populations perceive SCHIP as an "independence effect," others perceive it to be an "income effect," increasing their probability of marriage when they are covered by the health insurance and have a higher number of children. While SCHIP expansions (when made relevant to each mother by interacting it with her number of children) appear to adversely affect marital decisions, this result is not consistent across populations, particularly with the poorest groups in my dataset, who seem to experience this "income effect." The implication of this finding is that researchers and policy makers should be careful not to generalize on the effects of SCHIP and other health initiatives on marriage, and must acknowledge the complexity of incentives and decision-making in motherhood.

In 2000, the Assistant Secretary for Planning and Evaluation printed an article on the simulation of Medicaid and SCHIP eligibility. The authors of the article stressed the particular difficulties of estimating SCHIP eligibility, claiming that as the program often uses monthly income data, anti-crowd out waiting periods, and a variety of different income tests, disregards, and family composition rules among and within states. While these authors recommend the Survey of Income and Program Participation (SIPP) as best able to capture the complexities of SCHIP and Medicaid eligibility, I have attempted to use the more traditional March CPS Data, and through an analysis of different populations in the survey, sought to construct a reasonable model for assessing the effects of state generosity on marriage probabilities, in lieu of estimating an exogenous eligibility variable for each mother in the sample. Because my analysis uses a broad, state-level measure of generosity (FPL coverage levels), slightly modified by the mother's number of children in each age group, I cannot fully capture the direct relevance of SCHIP and other public health initiatives and their precise effect on a specific mother's family structure decision making. While I believe that my research provides very interesting results (for different population groups) and a valuable framework for future explorations into the effects of SCHIP and other health insurance on the probability of marriage, further research needs to be conducted on this topic, and it would be of great use if SIPP data (which would provide more precise measures of marriage and eligibility, etc.) were implemented in future projects.

Whether the government should act to prevent the dissolution of marriage as the side effect of programs such as SCHIP is beyond the scope of the paper. Regardless of which side one takes on this issue, the findings presented in this paper should come as a surprise, and may reflect different marriage probabilities for a different group of mothers that SCHIP and Medicaid have eventually expanded to cover. From the results of this study, a few main points should be made clear: the effects of health care insurance requires more scholarly attention, and that this scholarly attention needs to be consistent, especially since the same cannot be said for the effects of government programs over time.

References

HHN. (2004). Cash-strapped states forced to tighten Medicaid, SCHIP belts; look to feds to chip in. *H & HN*, 79.

Becker, Gary (1981). *A Treatise on the Family*. Cambridge; Harvard University Press.

Bitner, M. P. et al (2004). The impact of Welfare Reform on Marriage and Divorce. *Demography*, 41 (2), 213-235.

Broaddus, M., Blaney, S., Dude, A., Guyer, J., Ku, L. & Peterson, J. (2002). Expanding Family Coverage: States' Medicaid Eligibility Policies for Working Families in the Year 2000. *Center on Budget and Policy Priorities*., (2002).

Dahl, M. (2005, April 5). Changes in Participation in Means-Tested Programs. The *Congressional Budget Office Website*. Retrieved December 5, 2005 from http://www.cbo.gov/showdoc.cfm?index=6302&sequence=0

Gennetian, L., & Knox, V. (2004). The effects of a Minnesota Welfare Reform Program on marital stability six years later. *Population Research and Policy Review*, 23, 568-593.

Groeneveld, L., Hannan, M., & Tuma, N. (1980). The Effects of Negative Income Tax Programs on Marital Dissolution. *Journal of Human Resources* 15 (4), 654-74.

Hoynes, H. (1995). Does Welfare Play Any Role in Female Headship Decisions? National Bureau of Economic Research no. 5149.

Madigan, E. (2004, October 5). Medicaid is fastest-growing squeeze on state budgets. *Stateline*. Retrieved October 5, 2004, from http://www.stateline.org/live/ViewPage.action?siteNodeId=136&languageId=1&contentId=15794

Moffitt, R. (1994). Welfare Effects on Female Headship with Area Effects. *Journal of Human Resources* 29(2), 621-636.

Oppenheimer, V. K. (1997). Women's Employment and the Gain to Marriage: The Specialization and Trading Model. *Annual Review of Sociology*, 23, 431-53.

Winkler, A. (1995). Does AFDC-UP Encourage Two-Parent Families? *Journal of Policy Analysis and Management,* 14(1), 4-24.

Yelowitz, A. (1998). Will Extending Medicaid to Two-Parent Families Encourage Marriage? *Journal of Human Resources* 33(4), 833-865.

Appendix

Table 1
SCHIP Eligibility of Children Under 6 for 1997-2002 (by FPL Percentages)

State	1997	1998	1999	2000	2001	2002
Alabama	133	200	200	200	200	200
Alaska	133	133			200	200
Arizona	133	133	200	200	200	200
Arkansas**	200	200				200
California***	133	200	250	250	250	250
Colorado	133	185	185	185	185	185
Connecticut	185	300	300	300	300	300
Delaware	133	133	200	200	200	200
DistrictofColumbia	133	200			200	200
Florida	133	185	200	200	200	200
Georgia	133	200	200	235	235	235
Hawaii	300	300			200	200
Idaho	133	160			150	150
Illinois	133	185	185	185	185	185
Indiana	133	150		200	200	200
Iowa	133	133	185	200	200	200
Kansas	133	133	200	200	200	200
Kentucky	133	200	200	200	200	200
Louisiana	133	133			200	200
Maine	133	185	200	200	200	200
Maryland	133	200			300	300

Massachusetts	133	200	200	200	200	200
Michigan	150	200	200	200	200	200
Minnesota	275	275				
Mississippi	133	133			200	200
Missouri	133	300			300	300
Montana	133	150	150	150	150	150
Nebraska	133	185			185	185
Nevada	133	200	200	200	200	200
NewHampshire	185	300	300	300	300	300
NewJersey	133	200	200	350	350	350
NewMexico	185	235			235	235
NewYork	222	222	192	250	250	250
NorthCarolina	133	200	200	200	200	200
NorthDakota	133	133	140	140	140	140
Ohio	133	150				200
Oklahoma	133	185			185	185
Oregon	133	170	170	170	170	170
Pennsylvania	133	235	235	235	235	235
RhodeIsland	250	250				
SouthCarolina	133	150			150	150
SouthDakota	133	133		200	200	200
Tennessee	400	400			200	200
Texas	133	133	200	200	200	200
Utah	133	200	200	200	200	200
Vermont	225	300	300	300	300	300
Virginia	133	185	185	185	200	200
Washington	200	200	250	250	250	250
WestVirginia	133	133			200	200
Wisconsin	185	200			200	200
Wyoming	133	133			133	133

Source: MCH Updates 1998-2002 from the National Governor's Association (NGA)

Table 2
SCHIP Eligibility of Children Ages 6-18 for 1997-2002 (by FPL Percentages)

State	1997	1998	1999	2000	2001	2002
Alabama	100	200	200	200	200	200
Alaska	100	100			200	200
Arizona	100	100	200*	200	200	200
Arkansas**	200	200				200
California***	100	200	250	250	250	250
Colorado	100	185	185	185	185	185
Connecticut	185	300	300	300	300	300
Delaware	100	100	200	200	200	200
DistrictofColumbia	100	200			200	200
Florida	100	185	200	200	200	200
Georgia	100	200	200	235	235	235
Hawaii	300	300			200	200
Idaho	100	160			150	150

Illinois	100	185	185	185	185	185
Indiana	100	150		200	200	200
Iowa	100	133	185	200	200	200
Kansas	100	100	200	200	200	200
Kentucky	100	200	200*	200	200	200
Louisiana	100	100			200	200
Maine	125	185	200	200	200	200
Maryland	100	200			300	300
Massachusetts	133	200	200	200	200	200
Michigan	150	200	200	200	200	200
Minnesota	275	275				
Mississippi	100	100	133	133	200	200
Missouri	100	300			300	300
Montana	100	150	150	150	150	150
Nebraska	100	185			185	185
Nevada	100	200	200	200	200	200
NewHampshire	185	300	300	300	300	300
NewJersey	100	200	350	350	350	350
NewMexico	185	235			235	235
NewYork	185	222	192	250	250	250
NorthCarolina	100	200	200	200	200	200
NorthDakota	100	100	140	140	140	140
Ohio	100	150				200
Oklahoma	100	185			185	185
Oregon	100	170	170	170	170	170
Pennsylvania	100	185	235	235	235	235
RhodeIsland	250	250			250	250
SouthCarolina	100	150			150	150
SouthDakota	100	133		200	200	200
Tennessee	400	400			200	200
Texas	100	100	200	200	200	200
Utah	100	200	200	200	200	200
Vermont	225	300	300	300	300	300
Virginia	100	185	185	185	200	200
Washington	200	200	250	250	250	250
WestVirginia	100	100	150	150	200	200
Wisconsin	100	200			200	200
Wyoming	100	100	133	133	133	133

*In 2001, there was a distinction between FPL thresholds for Children ages 6-15 and children ages 15-18. As it turns out, the numbers are virtually identical, except in the case of Arizona and Kentucky. Arizona's upper teenager group had an FPL threshold of 100, whereas Kentucky's 15 and older category had an FPL limit of 150 percent.
NOTE: In 1997-1998, several states only covered children to a maximum age less than 18. For 1997, these states were: (14) Alabama, Arizona, California, Colorado, District of Columbia, Florida, Idaho, Illinois, Iowa, Kentucky, Louisiana, Maryland, Mississippi, Montana, Nebraska, Nevada, New Jersey, Ohio, Oklahoma, Pennsylvania, South Carolina, Texas, Wisconsin, Wyoming; (16) Connecticut, Michigan; (17) Kansan, Massachusetts, Tennessee, and Vermont. In 1998, these states were: (14) Alaska, Arizona, Louisiana, Mississippi, Wyoming; (15) Oklahoma; (16) Pennsylvania; (17) Kansas, and Vermont