PRELIMINARY

The Dynamics of Children’s Health Insurance, 1986-1999

John C. Ham
University of Southern California and IZA

Xianghong Li
York University

Lara Shore-Sheppard
Williams College and NBER

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Using data from the Survey of Income and Program Participation 1986-1996 panels, we provide both descriptive and analytical evidence about the dynamics of children’s health insurance between 1986 and 1999. We find that insurance turnover increased during this period, with a marked increase in transitions involving public insurance (Medicaid and the State Children's Health Insurance Program (SCHIP)). Our preliminary estimates of discrete time duration models for transitions of children’s insurance coverage across the insurance states of public insurance, private insurance, and no insurance show that several of the policy changes that took place over the 1990s had important effects on health insurance transitions for children. We find evidence that the implementation of Temporary Assistance to Needy Families, though not welfare waivers nor the expansion of the Earned Income Tax Credit (EITC), tended to reduce public insurance obtained through welfare participation. In the case of insurance obtained while not on welfare, we find strong and consistent evidence that the expansions of Medicaid and the implementation of SCHIP increased transitions out of uninsurance. Better economic conditions also tend to increase transitions out of uninsurance, particularly transitions to private insurance. We find evidence that higher health care costs tend to reduce the frequency of transitions–both transitions into insurance and transitions out of insurance, and weak evidence that increases in the EITC increase transitions to private insurance.

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I. Introduction

Over the past two decades, health insurance coverage for children has become an important focus of public policy. Recognition that individuals without health insurance are less likely to have a regular source of care or receive sufficient care has led to concern about the adequacy of health insurance coverage for members of a vulnerable population. The potential impact on coverage of rising health insurance premiums and other changes in health insurance markets have also increased policy attention on the issue of children's health insurance coverage. Falling levels of private coverage among children through the late 1980s and early 1990s spurred increased public provision of insurance, most notably expansions in eligibility for Medicaid and the introduction of the State Children's Health Insurance Program (SCHIP).

The past ten years have also seen significant changes in the welfare system and other policies that may affect children's health insurance coverage. Health insurance coverage among children is entwined with welfare participation and employment, as the two primary sources of insurance coverage for children are Medicaid (frequently obtained as an additional benefit of welfare participation) and coverage through a parent's employer. Policy changes such as welfare reform and expansions of the Earned Income Tax Credit (EITC) that are designed to encourage work may have secondary impacts on children's coverage as parents leave welfare for jobs that may or may not have health insurance coverage offered as a benefit. Similarly, changes in health care markets and economic conditions such as rising health care prices and cyclical changes in the availability of employment may also affect children's coverage.

While static models of insurance status among children have been estimated, there has been little attempt to characterize insurance dynamics, including spells of private insurance, public insurance (Medicaid/SCHIP), and uninsurance, among children. Dynamic models help us understand the process by which children become uninsured or gain insurance, allowing us to examine separately transitions between the three insurance states. Examining such transitions allows us to distinguish, for example, between a higher transition rate from private insurance to no insurance and reduced transitions out of no insurance. While both of these transition rates would be reflected in increased levels of uninsurance, they have different implications for policy. Dynamic models also permit us to account for the possibility that whether a child has insurance at a given time depends on that child's insurance coverage in a previous period.

In this paper, we use panel data from the Survey of Income and Program Participation (SIPP) to examine patterns of health insurance coverage among children during the period 1986-1999. Unlike most other panel data sets, the SIPP conducts interviews three times a year, allowing us to determine a child's insurance status at multiple points during the year. Using these data, we both provide a description of children's health insurance dynamics and estimate discrete time duration models for transitions of children's insurance coverage across three insurance states: public insurance, private insurance, and no insurance. We focus on the impacts of expansions in public coverage availability (expanded Medicaid and the introduction of SCHIP), the effects of other policies directed at the poor that affect employment and insurance coverage (including welfare reform and changes in the Earned Income Tax Credit), and economic conditions (as proxied by unemployment rates). Previous work on insurance dynamics has focused almost exclusively on adults. In addition, this work has tended to examine Medicaid spells or uninsured spells in isolation. We examine all three types of spells, including spells of private insurance. This is particularly important, as private insurance is the most prevalent source of insurance for children but levels of private coverage have fluctuated in recent years.

The paper proceeds as follows. In Section II we provide information on recent policy changes and discuss previous work. Section III describes the data set we use, the 1986-1996 panels of the SIPP. In Section IV we conduct a descriptive analysis of child insurance dynamics. We move to a more formal econometric model in Section V, outlining our proposed approach. Here we describe how we will account for problems of initial conditions, unobserved heterogeneity, endogenous explanatory variables such as welfare participation and employment status of the head of the family, and seam bias. In this draft of the paper, we do not maximize the entire likelihood function. Instead, we make the simplifying assumption of no heterogeneity and use an approximation that permits us to estimate the parameters of the different transition rates individually rather than jointly.

We discuss our empirical specification in Section VI and present our preliminary empirical results in Section VII. We find that several of the policy changes that took place over the 1990s had important effects on health insurance transitions for children. We find evidence that the implementation of Temporary Assistance to Needy Families, though not welfare waivers nor the expansion of the Earned Income Tax Credit (EITC), tended to reduce public insurance obtained through welfare participation. In the case of insurance obtained while not on welfare, we find strong and consistent evidence that the expansions of Medicaid and the implementation of SCHIP increased transitions out of uninsurance. Better economic conditions also tend to increase transitions out of uninsurance, particularly transitions to private insurance. We find evidence that higher health care costs tend to reduce the frequency of transitions–both transitions into insurance and transitions out of insurance, and weak evidence that increases in the EITC increase transitions to private insurance.

II. Policy Changes Affecting Children's Health Insurance

The 1990s were a period of great policy activity, and many of the changes that were made had implications for children's health insurance. Probably the most significant of these changes was the expansion of public health insurance for children whose families did not qualify for cash assistance. Prior to the late 1980s, Medicaid eligibility for children was tied to eligibility for Aid to Families with Dependent Children (AFDC). Generally, to qualify for AFDC a family must have been either headed by a single parent or (in some states) have an unemployed primary earner, and was required to pass stringent income and resource tests. Starting in the late 1980s, a series of federal law changes substantially diminished the link between Medicaid eligibility and AFDC eligibility by extending Medicaid coverage to pregnant women and children with incomes above the AFDC limits.[1] Under the expansions, Medicaid eligibility determination was different from AFDC eligibility determination in three fundamental ways: the eligibility limits were linked to the federal poverty line rather than to the AFDC limits, most of which were far below the poverty level, there were no family structure requirements, and eligibility was determined at the individual, rather than family, level.

The Medicaid expansions began in 1986 and continued through the early 1990s, with effective dates and phasing-in of the legislation making the dates of actual coverage changes somewhat later. Early legislation focused more on optional coverage–states were permitted to raise income limits above AFDC limits in order to extend Medicaid coverage to pregnant women, infants, and very young children. Later expansions required states to implement

[1]Until the expansions, the primary group eligible for Medicaid but ineligible for AFDC had been "Ribicoff children." States could choose to cover children who met the financial requirements for AFDC but did not qualify due to family structure–e.g., children from two-parent families or in privately subsidized foster care.

eligibility increases, and generally applied to older children. The most far-reaching required expansions took place as a result of the Omnibus Budget Reconciliation Acts (OBRA) of 1989 and 1990, which required states to cover pregnant women and children up to age 6 with family incomes up to 133 percent of the federal poverty level (in OBRA 1989) and to cover children born after September 30, 1983 with family incomes below 100 percent of the federal poverty level (in OBRA 1990).[2]

Following the Medicaid expansions, in 1997 the federal government chose to expand availability of public coverage further, establishing SCHIP, a block grant program that was designed to give states the means and flexibility to offer insurance coverage to more children. States responded by expanding their Medicaid programs further (typically by equalizing eligibility limits among children of different ages and raising the limits), implementing entirely new state-designed programs, or doing a combination of the two. Legislated eligibility limits increased further. These increases are evident in the first column of Table 1, which shows the average eligibility limits, as a percent of the federal poverty level, among children in each year of our data. Eligibility limits increased over the period from less than half the federal poverty line, on average, to around twice the federal poverty line by the end of the 1990s.

In addition to policies explicitly focused on health insurance, there was substantial policy activity surrounding work and welfare participation. Welfare reform, implemented by some states beginning in 1993 in the form of waivers of federal requirements and then implemented across the country with the passage of the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA), was generally intended to encourage welfare recipients to work.

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[2]See U.S. House of Representatives Committee on Ways and Means (1987-2000) for details of the Medicaid expansions. A summary of the expansions and their effective dates is also

Both “carrot” (e.g. increased earnings disregards) and “stick” (e.g. work requirements and time limits) policies were adopted. Such policies are likely to have an effect on children’s health insurance coverage, since they encourage families to leave the welfare rolls and begin work. One potential effect is to reduce Medicaid coverage for children, since participation in the AFDC program conferred automatic Medicaid coverage. However, to reduce the chance that children lost insurance, PRWORA required states to provide Medicaid coverage to any family that met the pre-PRWORA welfare eligibility limits. The other potential effect is on private coverage–as mothers began to work they increased their chances of obtaining health insurance through an employer. To the extent that former welfare recipients are unable to find jobs offering health insurance benefits, however, the impact on private coverage transitions may be small. Welfare reform is indicated in the data by the presence of a statewide waiver or the implementation of Temporary Assistance to Needy Families (TANF) in place of AFDC. The waivers were implemented in various states over the period 1993-1996, and “turn off” once the state has put its TANF program in place, which started in 1996 but was done in most states in 1997. Along with the changes in the program rules, there was a general reduction in the maximum cash benefit available to families with no earnings throughout the period studied, from slightly less than half the poverty line, on average, to a little more than a third.

Along with welfare reform, the mid- to late-1990s saw a substantial increase in the EITC The EITC increases the return to working since only workers are eligible for it, and initially the more the person works the more he or she is allowed to take home. The federal government increased the phase-in rate (the negative income tax rate) substantially, and many states followed suit with their own earned income credits. Over the period we study, the combined average

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available at http://lanfiles/williams.edu/~lshore/.

federal-state phase-in rate more than tripled. As a result of this change and changes in the phase-out rates, the maximum credit also rose, increasing more than six-fold between 1986 and 2000.

B. Previous Literature

Much of the previous work on health insurance dynamics has been descriptive in nature. Swartz and McBride (1990) and Swartz, Marcotte, and McBride (1993) use data from the 1984 panel of the SIPP to describe spells without health insurance for adults. Using data for which the beginning of the spell is observed in the data or for which the beginning date is known from retrospective information, they find that nearly half of all spells of uninsurance last for a short time (five months or less), but that nearly 20 percent of spells last more than two years.[3] Thus the time spent uninsured is bimodal, with the largest portion of the uninsured population spending only a short time uninsured, and a smaller but still sizable portion of the uninsured population remaining uninsured for a substantial period of time. Short, Cantor, and Monheit (1988) find similar results for Medicaid spells in the 1984 SIPP. While a majority of Medicaid enrollees were short-term participants in the program, long-term enrollees made up a substantial minority (43 percent of respondents ever on Medicaid were enrolled during the entire SIPP sample period). In addition, Short, Cantor, and Monheit use a univariate analysis to characterize how spells of Medicaid enrollment relate to individual characteristics. (Their analysis is univariate in the sense that they examine characteristics one at a time instead of looking at the effect of a variable holding other characteristics constant.) Of the spells that ended during the

[3] They must assume that there is no selection bias in terms of whom the information is available for, and that there is no unobserved heterogeneity in the hazard rates to combine information across spells in progress at the start of the sample and spells that begin after the start date of the sample. See Heckman and Singer (1984a) and Ham, Svejnar and Terrell (1998) for a discussion of this issue; the latter paper attempts to implement a possible means of relaxing this assumption with mixed success.

sample period, nearly half were associated with an improvement in the economic status of the respondent, although close to half of the former recipients were still poor and slightly over half became uninsured following their period of Medicaid coverage.

The two papers closest to our research are Berger and Black (1998) and Short and Freedman (1998). Berger and Black (1998) use administrative data on Medicaid recipients from Kentucky beginning in 1986. They estimate single spell duration models for the period 1986-1991 to analyze the length of time spent on Medicaid for different eligibility types (aged, blind, and disabled individuals receiving Supplemental Security Income; aged, blind, and disabled individuals who have "spent down" their assets to the medically needy level; AFDC recipients; and other eligible children). Berger and Black do not specifically investigate the effect of Medicaid expansions since the latest anyone could enter Medicaid in their sample was June 1987; also they only have data for Kentucky and thus the variation in Medicaid rules would be limited. Instead, they estimate duration models to characterize time spent on Medicaid by each of these populations. However an advantage of their paper is that unlike work using the SIPP (including ours), the beginning date of every Medicaid spell in their data is known. They find that the AFDC and other eligible children groups have shorter periods of Medicaid eligibility than the aged, blind, and disabled groups. In addition, they find that hazard rates for the AFDC and other eligible children groups are significantly affected by county economic conditions and urban area residence, as well as by demographic variables such as age and race.

Short and Freedman (1998) use duration models in seven waves of the 1990 SIPP to examine possible effects of hypothesized changes in Medicaid for single women. They consider movements across the insurance states of noninsurance, public insurance and private insurance, using the four-month interview interval as the unit of time. They include only one spell of a given type per woman and treat different spells for the same woman as independent. They conclude that most Medicaid spells during this period were relatively short, and that two-thirds of single women who left Medicaid became uninsured. Changes in insurance status among former welfare recipients were common. They find that more generous AFDC income limits led women to spend a longer time on Medicaid but not to enter Medicaid at a faster rate, with lower transitions to the uninsured state. They also find that higher income limits for pregnancy reduced transitions to uninsurance from both Medicaid and private coverage, and reduced transitions from Medicaid to private insurance. The most important differences between their study and our work are that Short and Freedman examine single women rather than children and they use only the 1990 SIPP while we use multiple panels, increasing the time period covered as well as the range of policies we can investigate. Also, our proposed methodology differs substantially from theirs.

In addition to these dynamic studies, there has been a substantial literature examining the impacts of various policy changes on health insurance coverage using cross-sectional approaches. Beginning in 1996, there has been a series of papers examining the effect of expanded public insurance eligibility on coverage. This literature has focused on "crowding out" of private coverage by expanded public coverage–the concern that increased eligibility for Medicaid or SCHIP may reduce private coverage. Most studies in this literature, including Cutler and Gruber (1996), Dubay and Kenney (1996), LoSasso and Buchmueller (2004), and Shore-Sheppard (2005) have used data from the Current Population Survey (CPS). These studies have estimated cross-sectional models of the relationship between public insurance eligibility and private coverage, public coverage, and no insurance, using the form of the expansions to identify the effects. The cross-sectional studies have found varying amounts of private coverage reduction attributable to the expansions, from no significant reduction to 50 percent, depending on the methodology and the time period studied, although the preponderance of evidence indicates that the degree of crowding out was slight (see Shore-Sheppard 2005 for a discussion of the merits of various approaches taken in the literature).

Other studies have used longitudinal data (though not the dynamic models used in this paper) to examine insurance coverage for children following the expansions, again focusing on insurance substitution. Yazici and Kaestner (2000) and Thorpe and Florence (1998) use data from the National Longitudinal Survey of Youth (NLSY), Blumberg, Dubay, and Norton (2000) use data from the 1990 SIPP, and Ham and Shore-Sheppard (2005) use data from the 1987-1993 SIPP panels.

Blumberg, Dubay, and Norton (2000) compare the change in insurance status for children who became eligible between the first and last interviews of the SIPP panel with the change for children who remained ineligible due to their age, controlling for characteristics of the children as of the first interview. Their estimate of the extent of substitution of public for private coverage is 23 percent for children who already had private coverage and 0 percent for children who began the panel uninsured. Although their focus is on displacement of private coverage by public coverage, in the process of examining displacement they estimate the probability that a child who is uninsured in the first interview is uninsured at the last interview. They find that this probability decreased among children whose age made them possibly affected by the expansions.

In previous work (Ham and Shore-Sheppard 2005), we have used the SIPP to estimate both cross-sectional models and simple panel data models. We allow the effect of eligibility for children who are newly eligible to differ from the effect for children who have been eligible for a period of time, since an eligible child may not be enrolled immediately in Medicaid. We find that children who have been eligible for Medicaid longer are more likely to be enrolled in Medicaid but are no more likely to have lost private coverage. We also estimate models including a lagged dependent variable, and find that insurance choice is quite persistent. The estimated long run impact of eligibility in the dynamic models is somewhat larger than the estimate from the static models, while the immediate impact of expanded Medicaid eligibility from the dynamic models is smaller than the estimated effect from the static models. These results suggest that a fully dynamic model, such as that conducted in this paper, will provide important insights into the mechanisms behind insurance movements.

Another relevant strand of literature is the work on the effects of welfare reform on health insurance coverage among potentially welfare-eligible women. Findings from this literature are somewhat conflicting, as Kaestner and Kaushal (2003), Bitler, Gelbach, and Hoynes (2005), and Cawley, Schroeder, and Simon (2005) find that welfare reform reduced the probability that a potentially welfare-eligible woman had insurance coverage, while Borjas (2003) and DeLeire, Levine, and Levy (2006) find that welfare reform either left health insurance coverage status unaffected or even increased the probability of having health insurance coverage (particularly for some demographic groups).

In our paper we focus on children rather than women, and analyze movements across three health insurance states: covered by private, covered by public, and uninsured. We begin by assembling descriptive evidence on coverage dynamics among children, and then move on to estimating formal models of insurance transitions.

III. Data

We use data from the Survey of Income and Program Participation (SIPP), a series of longitudinal data sets collected for a random sample of the U.S. population by the Census Bureau. The SIPP is collected in a series of panels, each one containing approximately 17,000 households, on average. For ease of interviewing, the entire sample is randomly split into four rotation groups, and one rotation group is interviewed each month. Each rotation group in a SIPP panel is interviewed once every four months about employment and program participation during the previous four months (termed a wave). We use the 1986, 1987, 1988, 1990, 1991, 1992, 1993, and 1996 panels, which cover the period from October 1985 to February 2000 (the 1989 panel is not used because it was ended after only three waves). The length of each SIPP panel varies: 28 months for the 1986 and 1987 panels, 24 months for the 1988, 32 months for the 1990 and 1991 panels, 40 months for the 1992 panel, 36 months for the 1993 panel, and 48 months for the 1996 panel. A new panel is introduced each year or every few years, which yields more than one panel with data covering a particular point in time.

Our analysis sample is composed of children who are younger than 19 years old, are not the head or spouse of their own family, and live in states that are identified in the SIPP (40 states and the District of Columbia are identified—the others are grouped for confidentiality). To address the possibility that our results may be driven by spurious transitions (for example when a child is erroneously coded as having public insurance in a given period although in fact he does not have public insurance in that period nor in the preceding or following periods), we recode the data to eliminate any spells of one month duration except for those occurring at the beginning or end of the sample period.

Another measurement issue in the SIPP is that of "seam bias." Census Bureau researchers have shown that there are a disproportionate number of transitions in the fourth (interview) month (see, e.g. Young 1989, Marquis and Moore 1990). The approach to this problem that has been used in the past is to use index functions or transition rates that apply to the four month period covered by the interview. However, this approach has the disadvantage that the information on the timing of transitions that reportedly occurred in months other than the seam month is lost. In this draft of the paper we use the data in monthly form and follow the suggestion of Ham, Li, and Shore-Sheppard (2006) of putting a dummy variable for the fourth month in each transition rate.

Using the state of residence information available in the SIPP, we link information from other sources to our data, including the Medicaid or SCHIP eligibility limits applying to each child, welfare and welfare reform variables, state-level Medicare expenditure data, the EITC maximum credit and initial phase-in rate applying to each family, the monthly unemployment rate in the state, and the minimum wage in the state. Means by year of each of these variables are in Table 1.

IV. An Overview of Children's Health Insurance, 1986-1999

Figures 1-3 show estimates of coverage or uninsured rates by month in the SIPP data. Each point in the figure is the mean rate for a month from a particular panel, calculated using the weight for the first year of the panel. Because the SIPP is composed of overlapping panels, most months have data from more than one panel. The data are sparse in early 1990 and 1995, however, as those years were only covered by at most one panel (the 1990 and 1993 panels, respectively). Another caveat is that since the SIPP, like all panel data sets, suffers from attrition, means from later in each panel are likely to be more noisy as they are estimated from fewer observations. In addition to plotting the estimated rates, we plot the trend smoothed using lowess and for comparison the same rates calculated using the March Current Population Survey. Since the questions asked in the SIPP and CPS are not the same, with SIPP asking about coverage at a point in time and the CPS asking about coverage over the entire previous year, we do not necessarily expect the levels to be the same, although we expect some similarity in the trends.[4]

According to the SIPP, uninsurance rates fell slightly in the early part of the period, were flat through the early 1990s, and then fell again at the end of the period. This trend is broadly consistent with the trend in the CPS data. Looking at the underlying types of coverage, it appears that the decline in uninsurance can be attributed to a slight increase in private coverage, with public coverage remaining flat. In the early 1990s, however, the flatness of the uninsurance trend masks significant changes in public and private coverage, with public coverage increasing substantially and private coverage declining. This was the period of the initial Medicaid expansions as well as a recession, and this figure makes clear why researchers focused on examining whether the expansions led to crowding out. At the end of the period, the fall in uninsurance appears to be due to increasing levels of private coverage that compensated for a decline in public coverage rates. While all three of the trends have some cyclical features, private coverage rates appear most clearly cyclical, declining during the slight recession of the

[4]Many researchers have noted that the CPS does not appear to be eliciting information about the entire previous year's coverage. See Swartz (1986) for a discussion of health insurance measurement issues in the CPS and Ham and Shore-Sheppard (2005) for a discussion of the SIPP versus the CPS and an attempt to reconcile the two.

early 1990s and rising during the economic boom of the late 1990s. This is not surprising, as private coverage is tied so closely to employment.

We next move from examining static coverage rates to investigating transitions. In Figure 4 we graph the rate at which transitions into insurance occur, while in Figure 5 we graph the rate of transitions to uninsurance. Over the 1986-1999 period, children appeared to gain and lose insurance at a fairly steady rate, despite the many changes in policy. The rate at which children gain insurance appears to have fallen slightly at the beginning and the end of the period, though the estimated rates are quite noisy, indicating that parents had more difficulty obtaining insurance for their children in these years. Between about 1991 and 1996, however, the entry rate appeared to rise slightly. Somewhat surprisingly, the pattern in insured to uninsured transitions is very similar to the insurance entry pattern, rather than mirroring it as one might expect if transitions out of insurance increased when transitions into insurance fell. Instead, both sets of transition rates appeared to rise slightly between 1991 and 1996, indicating an overall higher level of turnover in insurance during this period.

In order to understand transitions between the insured and uninsured states better, we next plot estimated transition probabilities for the six different types of transitions: no insurance to public insurance, no insurance to private insurance, public to none, public to private, private to none, and private to public, along with the probability of observing no transition at all. For clarity in the graph and to ensure that all of the transition probabilities are calculated using enough data, we average all of the observed transitions over the year for the first year of each SIPP panel (once again, because there was no panel in 1989, 1994, or 1995, we do not have estimates for those years).

The observation that turnover appeared to increase post-1991 is borne out in this graph, as the probability of no transition at all falls substantially. Looking at transitions by type, the increase in the transition probability appears to be due to an increase in transitions involving public insurance, with increases in all four types of transitions into and out of public coverage. Private-to-public transitions increased, but so did public-to-private. One possible explanation for this observed pattern is as public insurance eligibility was expanded further up the income distribution, a larger number of children had encounters with public coverage. Alternatively, as welfare reform further loosened the automatic nature of Medicaid enrollment, public coverage became more tenuous. We investigate these hypotheses further using our econometric model. Before turning to the model, however, it is informative to compare the transitions out of the various insurance states. This figure suggests that children who are in an uninsured spell are more likely to transition to public insurance and less likely to transition to private insurance at the end of the period. Similarly, children who are in a private insurance spell are less likely to lose coverage altogether than to replace their private coverage with public coverage. Finally, as noted previously both types of transitions out of public coverage increased.

V. Econometric Approach

A. Contribution to the Likelihood Function for Children from Two Parent Households

In this section we consider two cases: i) children from a family with two earners and ii) children from a single parent home. The situation for children in ii) is more complicated because it is possible that their family will go on welfare and thus automatically qualify the children for public insurance. Thus we consider case children in case i) first, and we assume family structure is exogenous. We need to describe transitions out of *fresh spells*—spells beginning after the start date of the sample—and *left censored spells*—spells in progress at the start date of the sample.

Define the transition intensity or transition rate (Lancaster 1990) for moving from a fresh spell of private insurance (that started at calendar time τ) to no insurance conditional on being on private insurance for t months as

(1a) $\lambda_{pni}(t\,|\,\bullet,\theta_{pni}) = \left[1+\exp-(h_{pn}(t)+\gamma_{1pn}X_i(t+\tau)+\gamma_{2pn}L_{is}(t+\tau)+\theta_{pni}\right]^{-1}.$

where $h_{pn}(t)$ denotes duration dependence, $X_i(t+\tau)$ is a vector of possibly time-changing explanatory variables at calendar time $t+\tau$ that capture demographic factors, economic conditions at $t+\tau$ and a measure of the cost of health services in the state at $t+\tau$, $L_{is}(t+\tau)$ represents the Medicaid/SCHIP income limits for the child in state s at $t+\tau$, and θ_{pni} is an unobserved heterogeneity component which is independent across children in different families but not necessarily across children in the same family.[5] Define the transition rate for moving from a fresh spell of private insurance to public insurance conditional on being on private insurance for t months as

(1b) $\lambda_{pmi}(t\,|\,\bullet,\theta_{pmi}) = \left[1+\exp-(h_{pm}(t)+\gamma_{1pm}X_i(t+\tau)+\gamma_{2pm}L_{is}(t+\tau)+\theta_{pmi}\right]^{-1}.$

(Note that the coefficient γ_{2pm} indicates the importance of "crowding out".) The overall probability of leaving private insurance is given by

(2) $\lambda_{pi}(t\,|\,\bullet,\theta_{pni},\theta_{pmi}) = \lambda_{pni}(t\,|\,\bullet,\theta_{pni}) + \lambda_{pmi}(t\,|\,\bullet,\theta_{pmi}).$

We define the transition intensities out of public insurance as

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[5] For ease of exposition in this draft we treat children from the same family as independent.

(3) $\lambda_{mki}(t\,|\,\bullet,\theta_{mki}) = \left[1+\exp-(h_{mk}(t)+\gamma_{1mk}X_i(t+\tau)+\gamma_{2mk}L_{is}(t+\tau)+\theta_{mki}\right]^{-1},\ k=p,n$

Finally, we define the transition intensities out of no insurance as

(4) $\lambda_{nki}(t\,|\,\bullet,\theta_{mki}) = \left[1+\exp-(h_{nk}(t)+\gamma_{1nk}X_i(t+\tau)+\gamma_{2nk}L_{is}(t+\tau)+\theta_{nki}\right]^{-1},\ k=p,m.$

Note that we would define the overall transition rate out of public insurance $\lambda_{mi}(t\,|\,\bullet,\theta_{mn},\theta_{mp})$, and the overall transition rate out of no insurance $\lambda_{ni}(t\,|\,\bullet,\theta_{np},\theta_{nm})$ analogously to (2).[6]

The density of a spell of no insurance of length t is given by

(5)
$$f_{ni}(t\,|\,\bullet) = \iint \prod_{r=1}^{t-1}(1-\lambda_{ni}(r\,|\,X_i(r+\tau),L_{is}(r+\tau),\theta_{np},\theta_{nm}))$$
$$\lambda_{ni}(t\,|\,t\,|\,X_i(t+\tau),L_{is}(t+\tau),\theta_{np},\theta_{nm})dG(\theta_{np},\theta_{nm})$$

where $G(\theta_{np},\theta_{mm})$ is the distribution function for $(\theta_{np},\theta_{mm})$. An interesting quantity for policy purposes is the expected duration of a spell of no insurance

(6) $ED_n(X_i,L_i) = \sum_{r=1}^{\infty} rf_i(r\,|\,\bullet)$,

where (X_i,L_i) represents the entire history of $X_i(r+\tau),L_{is}(r+\tau)$. The idea is that one can see how (6) changes as demographics, economic conditions, the cost of health care and state Medicaid/SCHIP income limits change for each individual.

To analyze our data, we must also consider the *left censored spells*, or the spells in progress at the start of the sample. These spells are difficult to analyze, particularly since we do not observe the length of the spells prior to the start of the sample.[7] To deal with them, we follow the pragmatic suggestion of Heckman and Singer (1984a) and give the transition rates for these

[6] To keep the notation manageable, we have dropped the 'i' subscript on the unobserved heterogeneity terms.

[7] While the SIPP survey attempts to record the start date of insurance spells, this

spells different parameters from the fresh spell transition rates. In some cases researchers discard these left censored spells. While this strategy is temptingly simple, excluding these spells can seriously bias the estimates of the fresh spell transition rates (Ham and LaLonde 1996), although Eberwein, Ham and LaLonde (1997) argue that the Ham and LaLonde result may be due to the special circumstances of the program they investigate (National Supported Work). Perhaps more importantly, time spent in the left censored spells constitutes a significant portion of all time spent in a health insurance state over the SIPP sample period, and this is especially true for the welfare durations we consider below for children from single families. Thus we also analyze the left censored spells.

We define the conditional transition intensity for leaving a left-censored spell in health insurance state j to move to state k analogously as

$$\text{(7)} \qquad \lambda_{j'k}(t \mid \bullet, \theta_{j'k}) = \left[1 + \exp-(h_{j'k}(t) + \gamma_{1j'k} X_i(t+\tau) + \gamma_{2j'k} L_{is}(t+\tau) + \theta_{j'k}\right]^{-1}$$

where $j' = n', m' p', k = n, m, p, k \neq j'$ and n' denotes a left censored no insurance spell, m' denotes a left censored public insurance spell and p' denotes a left censored private insurance spell.

Rather than writing a general expression for the likelihood function using the conditional transition intensities, we consider two examples. In Example 1 a child starts with no insurance. After $t_{n'}$ months she makes a transition to public insurance. She stays on public insurance until in month t_m of the spell, when she makes a transition to private insurance. She stays in private

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information is missing for most of the children in the data.

insurance for the remaining T_p periods. The density of the interrupted no insurance spell that ends in a transition to Medicaid is (conditional on the unobserved heterogeneity)

$$f_{n'}(t_{n'} \mid \bullet, \theta_{n'p}, \theta_{n'm}) = \prod_{r=1}^{t_{n'}} (1 - \lambda_{n'i}(r \mid X_i(r+\tau), L_{is}(r+\tau), \theta_{n'p}, \theta_{n'm})) \quad (8)$$
$$\lambda_{n'mi}(t_{n'} \mid X_i(t+\tau), L_{is}(t+\tau), \theta_{n'm})$$

where $\lambda_{n'i}(r \mid \bullet, \theta_{np}, \theta_{nm})$ is defined analogously to (2). The density of the spell on public insurance that ends in a transition to private insurance is

$$f_m(t_m \mid \bullet, \theta_{mp}, \theta_{mn}) = \prod_{r=1}^{t_{n'}} (1 - \lambda_{mi}(r \mid X_i(r+\tau), L_{is}(r+\tau), \theta_{mp}, \theta_{mn})) \quad (9)$$
$$\lambda_{mp}(t_{n'} \mid X_i(t+\tau), L_{is}(t+\tau), \theta_{mp}).$$

The density of the time spent on private insurance is

$$(10)\ S_p(T_p \mid \bullet, \theta_{pm}, \theta_{pn}) = \prod_{r=1}^{T_p} (1 - \lambda_{pi}(r \mid X_i(r+\tau), L_{is}(r+\tau), \theta_{pm}, \theta_{pn})).$$

The contribution to the likelihood is

$$L(t_{n'}, t_m, T_p) = \iiint\iiint f_{n'}(t_{n'} \mid \bullet, \theta_{n'p}, \theta_{n'm}) f_m(t_m \mid \bullet, \theta_{mp}, \theta_{mn}) S_p(T_p \mid \bullet, \theta_{pm}, \theta_{pn}) \quad (11)$$
$$dG(\theta_{n'p}, \theta_{n'm}, \theta_{mp}, \theta_{mn}, \theta_{pm}, \theta_{pn}).$$

In the Example 2 the child starts the sample period on Medicaid and stays there for the entire sample period T. Her contribution to the likelihood function is

$$(12)\quad L(T) = \iint S_{m'}(T \mid \bullet, \theta_{m'p}, \theta_{m'n}) dG(\theta_{m'p}, \theta_{m'n}).$$

Note that in general that the likelihood function for the overall sample will contain the parameters from the six left censored spell transition intensities and the six fresh spell hazard transition intensities, as well as the parameters of the heterogeneity distribution. Even if we have only 10 explanatory variables in each transition intensity and the heterogeneity distribution is a two point distribution, i.e. each realization of the unobserved heterogeneity takes one value with a probability P and another value with a probability (1-P) as in McCall (1996), this will leave 133 parameters to be estimated. For this draft we do not maximize the entire likelihood function. Instead we assume there is no heterogeneity, and we use the approximation

$$
\begin{aligned}
1-\lambda_{pi}(t\mid\bullet,\theta_{pni},\theta_{pmi}) \approx 1-\lambda_{pni}(t\mid\bullet,\theta_{pni})-\lambda_{pmi}(t\mid\bullet,\theta_{pmi}) \\
+((\lambda_{pni}(t\mid\bullet,\theta_{pni})*\lambda_{pmi}(t\mid\bullet,\theta_{pmi})),
\end{aligned} \tag{13}
$$

which allows us to estimate the parameters of the different transition rates separately using a standard software package.[8] In future work we will try to estimate all the parameters jointly. We discuss how we will do this and our proposed approaches to various problems such as seam bias in the rest of this section. Readers who are more interested in the empirical results that we have currently obtained may wish to move directly on to Section V.2.

One difficulty with estimating the parameters jointly is that for rich specifications of the hazard functions, the number of parameters may become prohibitive. Let μ_1, μ_2 and μ_3 be the parameters for the left censored spell transition intensities, the fresh spell transition intensities, and the parameters of the unobserved heterogeneity distribution respectively. We can write the likelihood function for the entire data set as $L(\mu_1, \mu_2, \mu_3)$ and the likelihood function of the left censored spells only as $L(\mu_1, \tilde{\mu}_3)$ where $\widehat{\mu}_3$ is a subset of μ_3. Note that we can estimate the parameters of the interrupted spells consistently by maximizing $L(\mu_1, \widehat{\mu}_3)$. Denote the estimate of μ_1 from this maximization by $\hat{\mu}_1$. We then maximize the likelihood $L(\hat{\mu}_1, \mu_2, \mu_3)$ with respect to μ_2 and μ_3, and denote these estimates by $\hat{\mu}_2$ and $\hat{\mu}_3$. All of these estimates are

[8] While we would not want to make this approximation in a final draft of the paper, our previous work and that of Jurajda (2004) indicates that it makes very little difference to the

consistent. We then take one step in a Newton-Raphson procedure around $L(\hat{\mu}_1, \hat{\mu}_2, \hat{\mu}_3)$ to obtain asymptotically efficient estimates $\tilde{\mu}_1, \tilde{\mu}_2, \tilde{\mu}_3$ and a consistent estimate of the appropriate variance-covariance matrix.

Thus far we have ignored the problem of seam bias in the SIPP. Individuals are interviewed every four months about the proceeding four months, and in the SIPP individuals report an unusually high number of transitions in month four of the period covered by the interview. Ham, Li and Shore-Sheppard (2006) propose a method for dealing with seam bias that involves parameterizing the reporting bias and incorporating the reporting bias into the likelihood function. Unfortunately, their method requires that one estimate left censored spells and fresh spells jointly even if there is no heterogeneity. Since we are estimating the spells separately in this draft, we cannot apply their approach in this draft. Instead we adopt their suggestion of putting a dummy variable for the fourth month in each transition rate.[9]

Once we have estimated these models, we can calculate the effect of various policy changes on the steady state probability of being in each insurance state. The steady state probabilities are given by (see Lancaster 1990, p. 114)

(14) $$P_p^* = (\lambda_n \lambda_m - \lambda_{nm} \lambda_{mn}) / c$$

and

(15) $$P_m^* = (\lambda_n \lambda_{\backslash p} - \lambda_{np} \lambda_{pn}) / c$$

where

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results.

[9] . When simulating the model, we do not use the coefficient on this dummy variable directly. Instead, we divide the estimate of the coefficient on this dummy variable by 4 and add

$$(16) \qquad c = \lambda_n \lambda_m - \lambda_{nm}\lambda_{mn} + \lambda_n \lambda_p - \lambda_{np}\lambda_{pn} + \lambda_p \lambda_m - \lambda_{pm}\lambda_{mp}\,.$$

Of course, the steady state probability of having no insurance is given by

$$(17) \qquad P_n^* = 1 - P_p^* - P_m^*.$$

One problem with the steady state probabilities is that they only depend on the fresh spell hazards. Therefore, one is implicitly assuming that sufficient time has progressed so that the interrupted spell hazards are not relevant. Given that an eight year old child only has a maximum of ten years of coverage remaining, it may be more appropriate to simulate the model and calculate short-run (e.g. one year), medium-run (e.g. five years) and long-run (e.g. 10 years) effects of policy expansions (as in Eberwein, Ham and LaLonde 1997, 2002) on the fraction of time spent in each insurance state than to consider the effect on the steady state probabilities. We will incorporate both of these calculations in future drafts. The idea is that one can see how the expected fraction of time in each state changes as demographics, economic conditions, the cost of health care and state Medicaid/SCHIP income limits change for each individual. For example, by considering changes in demand conditions holding the other policy variables constant will allow us to demonstrate the effect of business cycles on participation in different forms of health insurance. This latter effect will be both interesting in its own right and useful to policymakers for predicting public insurance caseloads.

B. Estimating the Effect of Endogenous Employment Status

The above specification is a reduced form one in the sense that it does not estimate the effect of employment for the husband or the wife in the family. We now consider estimating the effect of employment status on the transition rates. The identifying restriction is that the

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it to the constant.

employment status of the husband and wife in the family depend on a number of lags in the state unemployment rate while the current transition rates depend only on the current unemployment rate. Note that the employment status of the husband and wife will depend on lagged unemployment rates even if the transition rates from employment and unemployment depend only on the current demand conditions. Define a reduced form income equation

$$(18) \qquad Il^*_{lit} = \phi_l \tilde{X}_{it} + \sum_{j=0}^{K} \pi_{lj} UR_{st-j} + \theta_{el} + e_{lit}, \quad l = h, w.$$

Where h denotes husband, w denotes wife, UR_{st} is the unemployment rate in state s in period t and θ_e is an additional heterogeneity component correlated with the heterogeneity terms in the left censored and fresh spell transition rates. (We need $K \geq 2$ for identification.) Further, e_{lit} is an iid error term which is uncorrelated with the θ terms, has a known distribution function and $E(e_{hit}e_{wit}) = 0.$ Then the probability that a parent is employed conditional on is given by

$$(19) \quad \Pr(I_{lit} = 1 \mid \theta_{el}) = \Pr(I^*_{lit} > 0 \mid \theta_{el}) = \Pr(e_{lit} > -[\phi_l \tilde{X}_{it} + \sum_{j=0}^{K} \pi_{lj} UR_{st-j} + \theta_{el}]), \quad l = h, w.$$

In an obvious change of notation, we redefine all transition intensities conditional on eligibility as

$$(20) \quad \lambda_{j'k}(t \mid \bullet, \theta_{j'k}) = \begin{bmatrix} 1 + \exp-(h_{j'k}(t) + \gamma_{1j'k} X_i(t+\tau) + \gamma_{2j'k} L_{is}(t+\tau) \\ +\psi_{hj'k} I_{hit} + \psi_{wj'k} I_{wit} + \theta_{j'k} \end{bmatrix}^{-1},$$
$$j' = n', m', p', n, m, p, \quad k = n, m, p.$$

Suppose that the father and mother of the child in the first example above are employed for the first t_h and t_w periods respectively of the sample. (It is trivial to consider other employment histories.) Define

$$(21) \quad H_{hw}(t_h, t_w \mid \bullet, \theta_{eh}, \theta_{ew}) = \prod_{r=1}^{t_h} Pr(I_{hir} = 1 \mid \theta_{eh}) \prod_{r=t_h+1}^{T} (1 - Pr(I_{hir} = 1 \mid \theta_{eh})) \prod_{r=1}^{t_w} Pr(I_{wir} = 1 \mid \theta_{ew}) \prod_{r=t_w+1}^{T} (1 - Pr(I_{wir} = 1 \mid \theta_{ew})).$$

Then this child's contribution to the likelihood (which involves estimating the effect of parents' employment status directly) is given by

$$(22) \quad L(t_h, t_w, t_{n'}, t_m, T_p) = \iint \iiint \iiint H(t_h, t_w \mid \bullet, \theta_{eh}, \theta_{ew}) f_{n'}(t_{n'} \mid \bullet, \theta_{n'p}, \theta_{n'm}) f_m(t_m \mid \bullet, \theta_{mp}, \theta_{mn}) S_p(T_p \mid \bullet, \theta_{pm}, \theta_{pn}) dG(\theta_{eh}, \theta_{ew}, \theta_{n'p}, \theta_{n'm}, \theta_{mp}, \theta_{mn}, \theta_{pm}, \theta_{pn}).$$

where the integration is over the eight dimensional vector

$(\theta_{eh}, \theta_{ew}, \theta_{n'p}, \theta_{n'm}, \theta_{mp}, \theta_{mn}, \theta_{pm}, \theta_{pn})$ and we have redefined the densities, survivor function and distribution function in (22).

The likelihood function (22) has more parameters than (11) and thus will be even more difficult to maximize. However a multi-step procedure is also available here. First, estimate the parameters in (19) determining employment status. Second, conditional on these parameters estimate the parameters of the left censored spell transition rates from the data on the left censored spells (only). Third, conditional on the estimated parameters from (19) and the left censored spells, estimate the parameters of the fresh spell transition rates and the eight dimensional unobserved heterogeneity distribution. Finally, obtain one-step Newton-Raphson estimates.

If we want to allow for seam bias we can break the estimation into two steps. First, modify the employment contribution (19) for seam bias, and then estimate the parameters determining employment and the seam bias parameters for employment. (This modification is straightforward.) Second, conditional on these parameters, estimate the parameters for the left censored spells, the fresh spells and the seam bias parameters for insurance transitions. Then take a one-step Newton Raphson procedure.

C. Contribution to the Likelihood Function of Children from Female-Headed Households

In this section we consider children from single family homes since these families have the potential to be on welfare, and if on welfare, automatically qualify for Medicaid. Because of this, we do not analyze a child's health insurance status while his or her family is on welfare. Instead we only analyze their insurance dynamics when they are off welfare, and use the model described above for two parent families. Thus we will have the equivalent of a switching regression in a duration model. The on-welfare and off-welfare hazards determine whether the family is on welfare, and if they are off-welfare then they have the same insurance transition rates as the two-parent families considered above.[10] We define the hazard function for leaving welfare conditional on having been on welfare for the previous *t* periods as

$$(23)\qquad \begin{aligned}&\lambda_{ki}(t \mid X_i(t+\tau), B_{is}(t+\tau), \theta_{ki})\\ &= \left[1 + \exp -(h_k(t) + \gamma_{1k} X_i(t+\tau) + \gamma_{2k} B_{is}(t+\tau) + \theta_{ki}\right]^{-1}, k = w, w'.\end{aligned}$$

In equation (23) *w'* denotes a left censored on-welfare spell in progress at the start of the sample (with duration measured from the start of the sample), *w* denotes a fresh welfare spell which began after the start of the sample, and $B_{is}(t+\tau)$ reflects (maximum) welfare benefits in place in state s at calendar time $t+\tau$. The hazard function for leaving an off-welfare spell, (i.e. entering welfare), is given by

[10] One difference is that if the child moves to public insurance, we will count their previous time on welfare (and Medicaid) in calculation duration in the spell.

$$(24)\quad \begin{aligned}&\lambda_{ki}(t \mid X_i(t+\tau), B_{is}(t+\tau), \theta_{ki})\\ &= \left[1+\exp-(h_k(t)+\gamma_{1k}X_i(t+\tau)+\gamma_{2k}B_{is}(t+\tau)+\theta_{ki}\right]^{-1}, k = ow, ow'.\end{aligned}$$

In equation (31) o*w'* denotes a left censored off-welfare spell in progress at the start of the sample (with duration measured from the start of the sample) and o*w* denotes a fresh off-welfare spell which began after the start of the sample. The index function determining whether the child goes to public insurance when his or her family leaves welfare at calendar time t is given by

$$(25a)\quad M_{lt}^{*} = \phi_m X_{it} + \pi_m L_{sit} + \theta_m + v_{mit}.$$

Thus the probability that the child goes to public insurance is

$$(25b)\quad \Pr(M_{it} = 1 \mid \theta_m) = \Pr(M_{it}^{*} > 0 \mid \theta_m) = \Pr(v_{mit} > -[\phi_m X_{it} + \pi_m L_{sit} + \theta_m]).$$

The index function determining whether the child goes to public insurance when his or her family leaves welfare at calendar time t is given by

$$(26a)\quad P_{lt}^{*} = \phi_p X_{it} + \pi_p L_{sit} + \theta_p + v_{pit}.$$

The probability that the child goes to private insurance when the family leaves welfare at calendar time t is

$$(26b)\quad \Pr(P_{it} = 1 \mid \theta_p) = \Pr(P_{it}^{*} > 0 \mid \theta_p) = \Pr(v_{pit} > -[\phi_p X_{it} + \pi_p L_{sit} + \theta_p]).$$

For this draft we assume that v_{pit} and v_{mit} are independent, although it is straight-forward to relax this. Note that we would expect θ_p and θ_m to be negatively correlated although we will consider to assume no heterogeneity for this example.

We consider one simple example of constructing the contribution of a child from a female-headed family; in the next draft we will consider several other examples and use figures to increase the clarity of the presentation. For now consider a child whose family is in an left censored welfare spell for the first $t_{w'}$ months of the sample, at which point the family makes a transition off welfare. Assume that they stay off welfare for the remaining T_{ow} months of the sample. Suppose further that when the family leaves welfare (at calendar time t^*) the child is not covered by health insurance. The child stays without insurance for t_{np} months, at which point the child starts to be covered by private insurance. Finally the child stays on private insurance for the remaining T_p months of the sample. Then the child's contribution to the likelihood function is

$$
\begin{aligned}
& L(t_w, M_{t^*}=0, P_{t^*}=0, t_{np}, T_p) = \\
(27) \qquad & [\prod_{r=1}^{t_w-1}(1-\lambda_{w'i}(r\,|\,\theta_{w'}))\lambda_{w'i}(t_w\,|\,\theta_{w'})][\prod_{r=1}^{T_{ow}}(1-\lambda_{owi}(r\,|\,\theta_{ow}))] \\
& \iiiint \iiiint \Pr(M_{it^*}=0\,|\,\theta_m)\Pr(P_{it^*}=0\,|\,\theta_p)[\prod_{r=1}^{t_{np}-1}(1-\lambda_{ni}(r\,|\,\theta_{nm},\theta_{np}))\lambda_{npi}(t_{np}\,|\,\theta_{np})] \\
& [\prod_{r=1}^{T_p}(1-\lambda_p(r\,|\,\theta_{pn},\theta_{pm}))]dG(\theta_{w'},\theta_{ow},\theta_m,\theta_p,\theta_{nm},\theta_{np},\theta_{pn},\theta_{pm}).
\end{aligned}
$$

At this point readers not interested in technical estimation issues may want to proceed to section VI. Clearly we are now beginning to face a "curse of dimensionality," since in the overall likelihood there will be four transition rates from the welfare spells, two probability terms determining the health insurance state after the family leaves welfare, and twelve transition rates for the health insurance transitions off, and a corresponding number of unobserved heterogeneity terms. However, again two-step estimation is a possibility. Note that we are implicitly assuming that family structure is exogenous, and given this assumption we can estimate the parameters of the health insurance transition rates from the two parent families as described above. Further, we can estimate the welfare transition rates from the female headed households using only data on welfare participation. Conditional on these two sets of estimates, we then would estimate the parameters of the functions determining what type of insurance the child has going off welfare and the eighteen dimensional unobserved heterogeneity distribution. Finally, we would use a one-step Newton-Raphson procedure to obtain asymptotically efficient estimates of all parameters and consistent estimates of the standard errors for these estimates.

VI. Empirical Specification

As discussed above, we estimate discrete time hazard models of welfare entry and exit and transitions among the three insurance states. We specify each transition rate to be a function of duration, policy variables, variables characterizing economic and health market conditions, and demographic variables for the family head and the child. We expect the policy changes that expanded access to public insurance to increase the probability a child obtains public coverage, possibly at the expense of private coverage, while the policy changes restricting welfare are predicted to reduce the probability a child obtains public coverage through welfare. Expansions of the EITC and a higher minimum wage have ambiguous effects on insurance coverage–they increase the return to working, which may increase transitions into private coverage, but if the jobs obtained do not offer insurance to their workers, it is possible that transitions out of public coverage may increase while private coverage transitions remain unchanged. Increases in the unemployment rate are predicted to increase transitions out of private insurance, and to decrease transitions into private insurance from public insurance or from no insurance, as family heads are less likely to find jobs offering health insurance benefits. Health care price increases (which we proxy for with state-level Medicare expenditures per enrollee) may also have an ambiguous effect, with employees being more likely to value health insurance and therefore seek jobs offering it when prices are higher, but with employers and states being more likely to restrict access to coverage due to higher costs. We include year dummies to control for unobserved national-level insurance trends and macroeconomic shocks.

Demographic variables that increase a family head's earnings capability, such as age and education, are expected to increase transitions out of public insurance and reduce transitions into public insurance. We would also expect higher education levels to raise income and therefore increase the demand for private insurance–thus we would expect higher education to decrease the transition rate out of private insurance and increase the transition rate into private insurance. The demographic variables for race and ethnicity will affect transitions because they affect income. They may also reflect higher transaction costs of obtaining public insurance for Hispanics who do not have a good command of English or who may be concerned about immigration status. Following the literature we include family structure and the age of the child. The latter variable is important since the Medicaid/SCHIP income limits depend on the age of the child (as well as the time period and state of residence), and age may directly affect the transition rates if parents are reluctant to pay the transaction costs of enrolling their child in Medicaid if they only have a short period of eligibility, as will tend to be true for older children. Finally, we enter the sex of the child to see if parents perceive different benefits from enrolling a male child and a female child.

As discussed above, we consider eight different types of spells–"interrupted" (that is, spells in progress at the start of the sample) and "fresh" (spells observed to begin during the sample) welfare, public insurance, private insurance, and no insurance spells. Following our model, if a person reports being in a welfare spell, then he or she is not counted as being in a public insurance spell. Instead, the child's months on public insurance only contribute to the public insurance hazards after the child has left welfare (the duration of the public insurance spell is counted from the first point the person reports receiving public insurance, however, even if that is during the welfare spell). In about two percent of the person-months in the data, individuals report having both public and private insurance. Since it would be prohibitively complex to add a fourth state ("both public and private") to the model, we consider months with both to be part of a private insurance spell. In future drafts we will examine the robustness of this assumption to two alternative assumptions (considering months with both to be part of a public insurance spell, and dropping children who ever report having both types of coverage simultaneously).

Descriptive statistics by spell type are presented in Tables 2 and 3. The most common type of spell is an interrupted private insurance spell, which is not surprising given that private insurance coverage levels are much higher than public coverage or uninsured levels. Many children start the sample on private coverage and never leave it, which can be seen by comparing the number of right-censored spells with the total number of spells. Overall, private insurance spells tend to be longer than other tpes of spells, followed by public insurance spells and then no insurance spells. The spell lengths include right-censored spells, so mean elapsed duration of all kinds of spells would be considerably higher than the numbers shown here. Looking at the distribution of spell lengths, spells either seem to end fairly quickly–within 8 months–or to continue for a longer time.

Table 3 contains demographic characteristics of children in the data (as of the first month of each spell). Consistent with evidence from cross-sectional data, younger children, nonwhite children, children with less-educated or disabled family heads, and children in female-headed families or families with more children tend to be more likely to have public or no insurance. Unsurprisingly, children in private or uninsured spells have lower Medicaid and SCHIP eligibility levels. Children in welfare spells are also more likely to be nonwhite, to have a less-educated family head, to be in a female-headed household, or to have a disabled head, and much less likely to have anyone in their family working. The connection between private insurance and the labor market is clear: in 85% of the first months of fresh private insurance spells and 96% of the first months of interrupted private insurance spells the family has at least one earner. However, in 81 percent of the first months of fresh no insurance spells and 80 percent of the first months of interrupted no insurance spells the family had at least one earner, indicating that despite the connection to the labor force, the families were not obtaining insurance for their children through their employer.

VII. Empirical Results

Our preliminary empirical results (from the model assuming no heterogeneity and using the approximation in (13) are presented in Tables 4-7. For each type of state (welfare, no insurance, public insurance, and private insurance), we estimate separately the four transition intensities (interrupted and fresh entry into and exit from the state) using a logit model (the numbers in the table are logit coefficients). Turning first to the welfare models in Table 4, we find results that largely accord with our expectations. Higher welfare benefits tend to reduce the probability of exit from welfare and to increase the probability of entry, as do higher unemployment rates. Children in months and states where TANF has been implemented have a higher probability of leaving welfare, and a lower probability of starting welfare, although these results only hold for interrupted welfare and non-welfare spells. Surprisingly given the literature on welfare participation and the EITC (see Grogger 2004, for example), we find no relationship or (in the case of welfare entry from interrupted off-welfare spells) a perverse relationship between more generous EITC and welfare transition probabilities. Similarly, our results indicate no relationship or a perverse relationship between the presence of a welfare waiver and the probability of exiting from a fresh welfare spell. The demographic variables generally enter the model with the expected signs (though the coefficients are not always statistically different from 0)–children who are younger, nonwhite, Hispanic, in a single-parent family, in families with more children, and who have less educated or disabled family heads are less likely to exit welfare and more likely to enter. There is evidence of duration dependence in both welfare and non-welfare spells.

The models for the other three insurance states also show a reassuringly low rate of hard-to-explain signs for the demographic variables. Variables indicating that a family faces better labor market prospects tend to increase transitions to private insurance from both states and to reduce exits from private insurance and entries to no insurance and public insurance. More interesting are the policy parameters. As expected, higher Medicaid/SCHIP eligibility limits increase the probability of a transition to public insurance from both interrupted and fresh spells of no insurance, however they also appear to increase the probability of a transition to private insurance. This "crowding in" is difficult to explain except possibly as the result of policy endogeneity–states may be more likely to increase coverage when their economies are thriving. However, we control for unemployment rates (which have the expected negative sign for the transition to private insurance) which should account for such policy endogeneity. There is also some evidence of an effect of the expanded EITC, although the different EITC parameters, which would be expected to have similar effects, instead enter in opposite directions and only for interrupted none-to-private and fresh none-to-public transitions. Higher unemployment rates appear to reduce the probability of transitioning to private insurance from no insurance, as would be expected since higher unemployment rates make obtaining a job with health insurance benefits more difficult. Higher levels of Medicare spending per enrollee in a state, our proxy for higher health care costs, also reduce the probability a child gains insurance, although the effect is only statistically different from 0 in the case of transitions to private insurance from interrupted uninsured spells.

Higher levels of spending per enrollee also reduce transitions out of interrupted public insurance spells (Table 6), perhaps because parents are more concerned about maintaining their child's enrollment when health care costs are high. Similarly, worse economic conditions tend to increase transitions from public insurance to no insurance and reduce transitions to private insurance. Higher minimum wages and higher Medicaid/SCHIP eligibility limits have the opposite effect, reducing transitions out of public insurance to no insurance and increasing transitions to private insurance. The latter effect on public to private transitions may be a result of expanding public insurance eligibility up the income distribution, so that families with typically stronger attachment to the labor market spend some time in public insurance, leaving for private insurance rather than becoming uninsured. Once again the EITC variables have inconsistent effects, not allowing us to draw any firm conclusions about the impact of the EITC on health insurance coverage.

Finally, we examine exits from private insurance (Table 7). Here higher public insurance eligibility limits consistently increase transitions from private insurance to public insurance and reduce transitions to no insurance. This finding is consistent with crowding out, though it is also consistent with families who are being forced to leave private insurance for reasons other than the availability of public coverage choosing to enroll their children in public coverage rather than letting them become uninsured. Interestingly, none of the other policy variables enter in a statistically significant way, though once again the unemployment rate enters as expected, with higher unemployment rates increasing transitions to no insurance from both types of private insurance spells. As before, variables indicating greater attachment to the labor force tend to reduce all types of transitions from private insurance.

VIII. Conclusion

In this paper, we use data from the 1986-1996 SIPP panels to provide both descriptive and analytical evidence about the dynamics of children's health insurance between 1986 and 1999. We find that insurance turnover increased during this period, with a marked increase in transitions involving public insurance. Children who gained insurance were more likely to gain public insurance and less likely to gain private insurance at the end of the period than they were in the beginning. Also by the end of the period, children who lost private coverage became more likely to move into public coverage and less likely to lose coverage entirely.

Our preliminary estimates of discrete time duration models for transitions of children's insurance coverage across the insurance states of public insurance, private insurance, and no insurance show that in addition to demographic and family structure factors, several of the policy changes that took place over the 1990s had important effects on health insurance transitions for children. Examining welfare participation as the primary way for a child to obtain public insurance, not surprisingly we find that higher welfare benefits tend to reduce welfare exit and spur welfare entry, as do higher unemployment rates. However, we also find some evidence that the implementation of TANF (though not welfare waivers nor the expansion of the EITC) tended to increase welfare exit and reduce entry. In the case of insurance obtained while not on welfare, we find strong and consistent evidence that the expansions of Medicaid and the implementation of SCHIP (as proxied by higher income limits) increased transitions out of uninsurance, explaining the pattern we saw in the descriptive statistics. Better economic conditions (as proxied by lower unemployment rates) also tend to increase transitions out of uninsurance, particularly transitions to private insurance. We find evidence that higher health care costs (as proxied by higher spending on Medicare in a state) tend to reduce the frequency of transitions–both transitions into insurance and transitions out of insurance. Our evidence on the impact of the increased EITC is more mixed, but we do find some evidence that it may have increased transitions to private insurance.

In future drafts we will implement our feasible estimation scheme for dealing with problems of initial conditions, unobserved heterogeneity, endogenous explanatory variables, and seam bias. We will explore alternative specifications of the duration dependence, and will simulate the model to obtain short-run, medium-run and steady state effects of changes in policy variables and demand conditions.

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Figure 1.

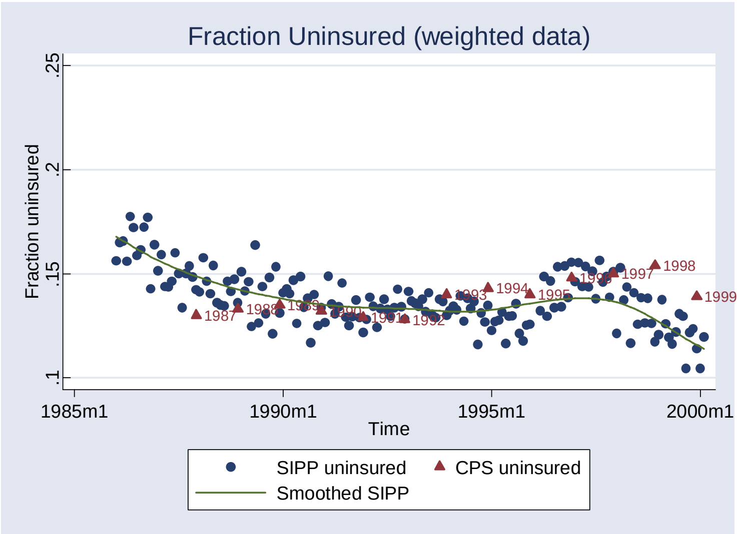

Figure 2.

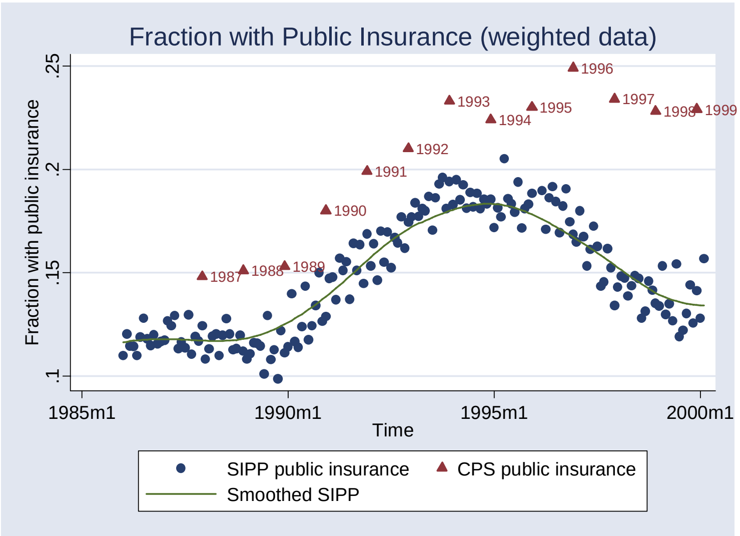

Figure 3.

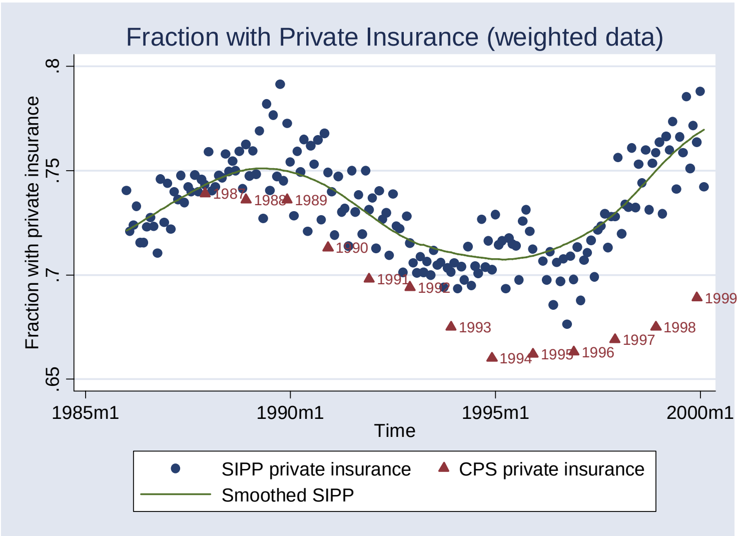

Figure 4.

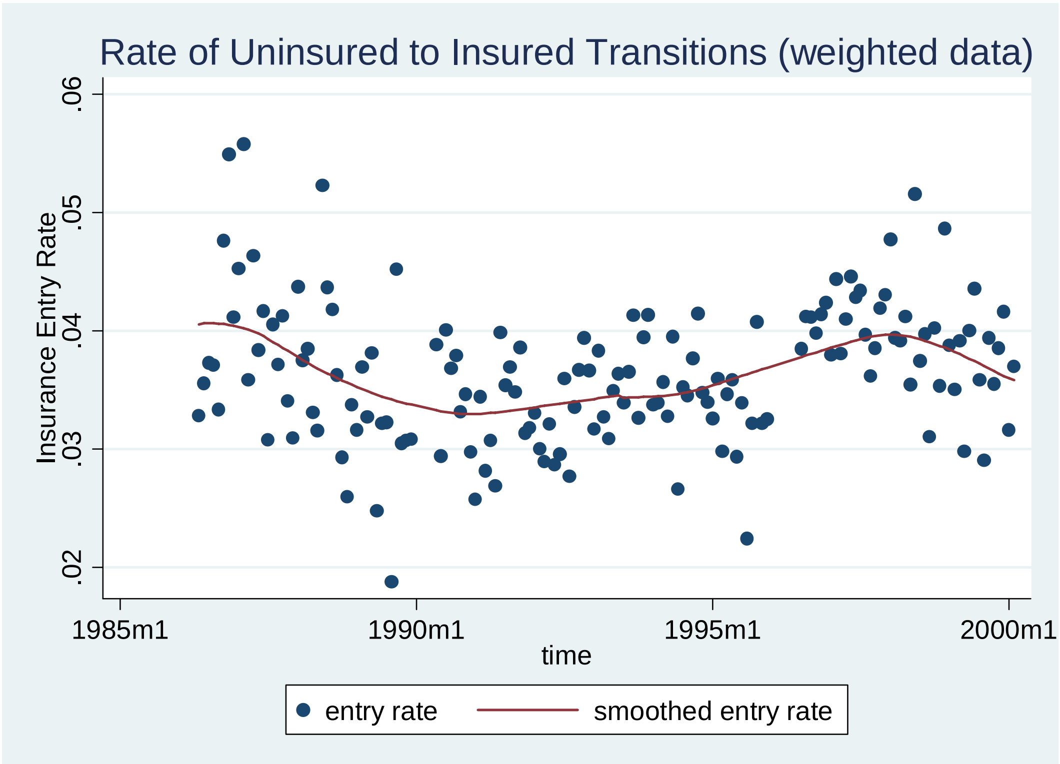

Figure 5.

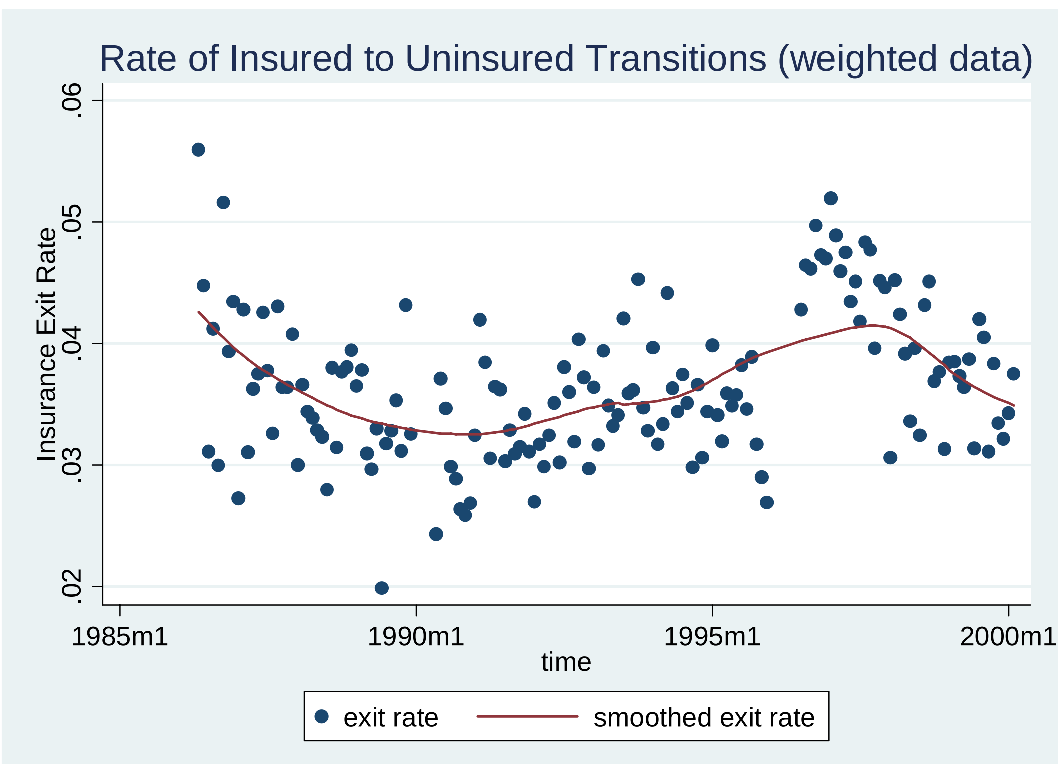

Figure 6: Transition Probabilities, First Years of SIPP Panels

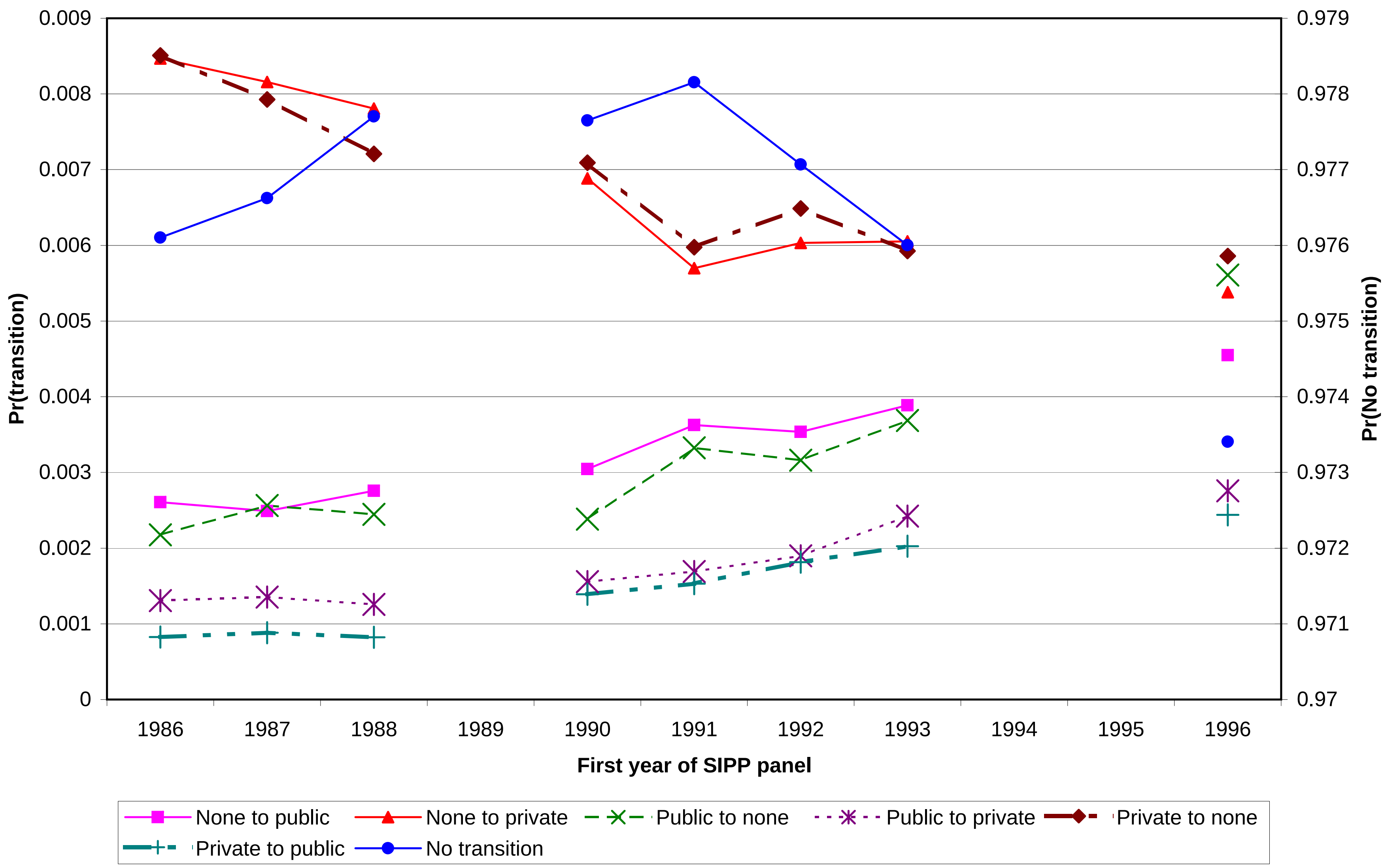

Table 1. *Means of Policy Variables, 1986-1996 SIPP*

Year	Medicaid/SCHIP elig. limit (%FPL)	Medicare exp. per enrollee	AFDC/TANF max. benefit (%FPL)	Major waiver implemented	TANF implemented	Fed. and state max. EITC credit	Fed. and state EITC phase-in rate	Unemployment rate	Minimum wage
1986	47.09	2410.65	47.19	0.00	0.00	548.82	10.98	7.06	3.35
1987	46.63	2539.89	46.63	0.00	0.00	855.97	13.97	6.30	3.36
1988	47.10	2709.66	45.78	0.00	0.00	878.53	13.96	5.70	3.43
1989	48.62	3026.44	44.13	0.00	0.00	923.83	14.10	5.44	3.52
1990	68.83	3241.83	43.10	0.00	0.00	965.58	14.08	5.68	3.81
1991	76.96	3463.00	42.13	0.00	0.00	1242.09	17.42	6.88	4.17
1992	89.06	3824.56	40.40	0.01	0.00	1390.13	18.40	7.60	4.28
1993	106.22	4086.69	38.27	0.23	0.00	1513.17	19.46	7.09	4.29
1994	109.31	4511.82	37.23	0.31	0.00	2469.42	29.64	6.20	4.30
1995	110.82	4944.68	36.32	0.36	0.00	2962.80	39.34	5.78	4.30
1996	105.76	5235.67	35.50	0.48	0.14	3305.92	39.55	5.51	4.43
1997	110.25	5487.42	34.11	0.04	0.93	3421.76	39.72	5.05	4.42
1998	157.50	5557.85	34.06	0.00	1.00	3534.58	39.76	4.58	4.78
1999	193.37	5432.49	34.48	0.00	1.00	3604.67	39.82	4.29	4.95
2000	208.24	5621.76	34.01	0.00	1.00	3699.23	40.12	4.07	5.01

Means are calculated over all person-months in the indicated year, and are weighted using the weights for the first year of the panel.

Table 2. *Welfare and Insurance Spells, 1986-1996 SIPP*

	Welfare Spells		Public Insurance Spells		Private Insurance Spells		No Insurance Spells	
	Interrupted Spells	Fresh Spells	Interrupted Spells	Fresh Spells	Interrupted Spells	Fresh Spells	Interrupted Spells	Fresh Spells
Number of Spells	11908	9032	19319	15997	84959	25212	19970	29757
Number of right-censored	6502	4322	10295	7285	70941	14567	8606	12125
Mean length (months)	16.7	8.77	16.07	8.66	23.67	9.88	12.39	6.63
(Standard deviation)	(12.3)	(7.5)	(12.19)	(7.46)	(13.74)	(8.79)	(10.93)	(6.09)
Spell distribution (%)								
1-4 months	23.54	45.58	16.57	46.38	9.89	44.69	24	60.79
5-8 months	16.3	21.67	21.23	21.35	11.13	18.21	27.5	18.13
9-12 months	10.12	12.08	12.87	11.35	7.79	10.87	12.83	8.97
13-16 months	7.73	7.03	8.71	7.7	6.24	7.39	8.13	4.77
17-20 months	6.83	5.18	7.1	5.11	5.86	6.04	5.73	3.24
21-24 months	7.92	3.48	7.39	3.18	10.51	4.45	6.12	1.75
25-28 months	5.84	2.6	5.52	2.36	7.57	3.53	3.99	1.1
> 28 months	21.72	2.38	20.61	2.59	41.02	4.81	11.7	1.25

Spell length is the length observed in the sample, and is calculated for both spells observed to end in the data and right-censored spells.

Table 3. *Individual Characteristics, by Type of Spell, 1986-1996 SIPP*

	Welfare Spells		Public Insurance Spells		Private Insurance Spells		No Insurance Spells	
	Interrupted Spells	Fresh Spells	Interrupted Spells	Fresh Spells	Interrupted Spells	Fresh Spells	Interrupted Spells	Fresh Spells
Age	6.15	7.12	5.56	7.02	7.95	8.28	7.83	8.21
Male	0.51	0.51	0.51	0.52	0.52	0.52	0.52	0.51
Black	0.41	0.34	0.34	0.26	0.11	0.22	0.18	0.20
Other Race	0.07	0.04	0.06	0.05	0.04	0.06	0.05	0.05
Hispanic	0.22	0.22	0.24	0.28	0.09	0.19	0.26	0.19
Age of the Head	30.67	32.16	30.57	32.90	36.85	34.62	34.59	35.26
Education of the Head	10.82	11.03	10.86	10.94	13.45	11.78	11.18	11.85
Head Disabled	0.22	0.25	0.20	0.20	0.10	0.15	0.14	0.16
Female Head	0.81	0.67	0.68	0.51	0.15	0.39	0.33	0.37
Male Only Head	0.02	0.03	0.03	0.04	0.03	0.04	0.06	0.05
One Earner	0.17	0.31	0.30	0.46	0.39	0.48	0.50	0.47
Two Earners	0.03	0.08	0.07	0.14	0.57	0.37	0.30	0.34
Number of Children	2.80	2.66	2.65	2.56	2.22	2.36	2.41	2.38
Medicaid/SCHIP Elig. Lim.	103.97	111.50	112.45	118.73	88.85	101.90	86.14	107.61
AFDC Max Benefit	44.57	39.69	41.88	38.09	41.74	38.43	38.61	37.78
Number of People	11908	7719	19319	12541	84959	21050	19970	23999

Table 4. *Welfare Exits and Entries, 1986-1996 SIPP*

	Welfare exit		Welfare entry	
	Interrupted	Fresh	Interrupted	Fresh
AFDC/TANF maximum benefit	-0.015	-0.006	0.004	0.012
(%FPL)	(0.001)**	(0.001)**	(0.001)**	(0.001)**
Major AFDC waiver implemented	0.057	-0.190	-0.073	-0.094
	(0.051)	(0.062)**	(0.048)	(0.073)
TANF implemented	0.385	0.163	-0.237	0.101
	(0.094)**	(0.103)	(0.107)*	(0.133)
Federal and state maximum	0.076	-0.079	-0.045	-0.043
EITC credit (/$1000)	(0.080)	(0.076)	(0.066)	(0.096)
Federal and state EITC initial	-0.013	0.013	0.028	-0.008
phase-in rate	(0.013)	(0.012)	(0.010)**	(0.015)
Unemployment rate	-0.084	-0.039	0.090	0.006
	(0.011)**	(0.013)**	(0.010)**	(0.016)
Minimum wage rate	0.012	0.038	0.070	-0.025
	(0.044)	(0.044)	(0.048)	(0.046)
Age	0.042	0.028	-0.043	-0.021
	(0.004)**	(0.004)**	(0.003)**	(0.005)**
Male	0.052	-0.040	-0.017	-0.027
	(0.029)	(0.033)	(0.027)	(0.039)
Black	-0.302	-0.170	0.663	0.292
	(0.033)**	(0.038)**	(0.034)**	(0.046)**
Other race	-0.667	-0.210	0.283	0.275
	(0.072)**	(0.081)**	(0.074)**	(0.092)**
Hispanic	-0.162	-0.071	0.169	0.080
	(0.040)**	(0.045)	(0.041)**	(0.057)
Family has single female head	-0.787	-0.573	1.778	0.438
	(0.043)**	(0.040)**	(0.033)**	(0.049)**
Family has single male head	-0.079	-0.228	1.039	0.487
	(0.116)	(0.102)*	(0.073)**	(0.118)**
Number of children in family	-0.142	-0.033	0.210	0.140
	(0.012)**	(0.013)*	(0.011)**	(0.015)**
Family head's education	0.052	0.037	-0.153	-0.064
	(0.007)**	(0.007)**	(0.005)**	(0.008)**
Family head disabled	-0.364	-0.331	0.881	0.443
	(0.036)**	(0.040)**	(0.035)**	(0.046)**
Age of family head	-0.006	0.001	-0.049	-0.007
	(0.002)**	(0.002)	(0.003)**	(0.003)*
Duration (months)	-0.032	-0.033	-0.050	-0.103
	(0.002)**	(0.003)**	(0.002)**	(0.004)**
Observations	192422	74839	2659379	107503

Robust standard errors in parentheses (* significant at 5%; ** significant at 1%)

In addition to the variables shown, all models include a constant, a set of year dummies, and a dummy for the fourth month of the wave. Standard errors have been corrected for the presence of multiple observations/person.

Table 5. *Exits from No Insurance, 1986-1996 SIPP*

	Interrupted no insurance spells		Fresh no insurance spells	
	To Public	To Private	To Public	To Private
Medicaid/SCHIP eligibility limit	0.004	0.001	0.002	0.001
	(0.000)**	(0.000)**	(0.000)**	(0.000)**
Federal and state maximum	0.018	0.200	-0.183	0.064
EITC credit (/$1000)	(0.095)	(0.070)**	(0.069)**	(0.052)
Federal and state EITC initial	-0.013	-0.026	0.037	-0.008
phase-in rate	(0.015)	(0.011)*	(0.011)**	(0.008)
Unemployment rate	0.018	-0.060	0.012	-0.037
	(0.015)	(0.009)**	(0.014)	(0.008)**
Minimum wage rate	-0.002	0.017	-0.028	0.019
	(0.054)	(0.040)	(0.035)	(0.026)
Medicare expenditures	-0.038	-0.100	-0.043	-0.003
per enrollee (/$1000)	(0.033)	(0.023)**	(0.028)	(0.018)
Age	-0.046	0.018	-0.045	0.019
	(0.005)**	(0.003)**	(0.004)**	(0.003)**
Male	0.011	-0.004	-0.018	-0.000
	(0.037)	(0.025)	(0.032)	(0.022)
Black	0.289	0.005	0.206	-0.104
	(0.050)**	(0.035)	(0.041)**	(0.029)**
Other race	-0.052	-0.247	0.176	-0.162
	(0.094)	(0.056)**	(0.076)*	(0.053)**
Hispanic	0.155	-0.277	0.015	-0.241
	(0.046)**	(0.034)**	(0.046)	(0.031)**
Family has single female head	0.566	-0.112	0.441	-0.240
	(0.043)**	(0.030)**	(0.036)**	(0.026)**
Family has single male head	0.133	-0.082	-0.041	-0.182
	(0.090)	(0.057)	(0.086)	(0.054)**
Number of children in family	0.049	-0.159	0.150	-0.087
	(0.014)**	(0.011)**	(0.014)**	(0.010)**
Family head's education	-0.052	0.089	-0.081	0.105
	(0.007)**	(0.005)**	(0.006)**	(0.005)**
Family head disabled	0.491	-0.205	0.504	-0.309
	(0.050)**	(0.038)**	(0.042)**	(0.032)**
Age of family head	-0.025	-0.008	-0.020	0.004
	(0.003)**	(0.002)**	(0.003)**	(0.002)*
Duration (months)	0.004	-0.002	-0.047	-0.065
	(0.002)	(0.002)	(0.003)**	(0.002)**
Observations	245062	245062	200978	200978

Robust standard errors in parentheses (* significant at 5%; ** significant at 1%)
In addition to the variables shown, all models include a constant, a set of year dummies, and a dummy for the fourth month of the wave. Standard errors have been corrected for the presence of multiple observations/person.

Table 6. *Exits from Public Insurance, 1986-1996 SIPP*

	Interrupted public insurance spells		Fresh public insurance spells	
	To None	To Private	To None	To Private
Medicaid/SCHIP eligibility limit	-0.002	0.000	-0.002	0.001
	(0.000)**	(0.000)	(0.000)**	(0.000)**
Federal and state maximum	0.018	-0.265	-0.116	0.053
EITC credit (/$1000)	(0.077)	(0.102)**	(0.082)	(0.101)
Federal and state EITC initial	0.003	0.042	0.007	0.011
phase-in rate	(0.012)	(0.016)**	(0.014)	(0.016)
Unemployment rate	0.042	-0.048	0.009	-0.050
	(0.012)**	(0.016)**	(0.013)	(0.018)**
Minimum wage rate	-0.011	0.146	-0.094	0.074
	(0.047)	(0.070)*	(0.037)*	(0.052)
Medicare expenditures	-0.105	-0.090	-0.010	0.008
per enrollee (/$1000)	(0.027)**	(0.036)*	(0.027)	(0.034)
Age	0.009	0.021	0.019	0.023
	(0.004)*	(0.006)**	(0.004)**	(0.005)**
Male	-0.060	0.072	-0.015	0.049
	(0.032)	(0.044)	(0.032)	(0.043)
Black	-0.087	-0.091	0.082	0.098
	(0.041)*	(0.056)	(0.043)	(0.054)
Other race	0.031	-0.132	0.021	0.161
	(0.074)	(0.109)	(0.076)	(0.101)
Hispanic	0.117	-0.395	0.190	-0.193
	(0.041)**	(0.064)**	(0.042)**	(0.059)**
Family has single female head	-0.007	-0.255	-0.184	-0.050
	(0.036)	(0.051)**	(0.038)**	(0.049)
Family has single male head	0.289	-0.503	0.219	-0.151
	(0.084)**	(0.137)**	(0.082)**	(0.123)
Number of children in family	-0.064	-0.072	-0.008	-0.100
	(0.013)**	(0.019)**	(0.014)	(0.020)**
Family head's education	-0.011	0.088	-0.022	0.101
	(0.006)	(0.011)**	(0.006)**	(0.010)**
Family head disabled	-0.041	-0.291	-0.155	-0.358
	(0.043)	(0.062)**	(0.042)**	(0.061)**
Age of family head	-0.010	-0.014	-0.007	-0.006
	(0.002)**	(0.004)**	(0.002)**	(0.003)
Duration (months)	0.005	0.003	-0.024	-0.048
	(0.002)**	(0.003)	(0.003)**	(0.004)**
Observations	113689	114071	90323	90323

Robust standard errors in parentheses (* significant at 5%; ** significant at 1%)
In addition to the variables shown, all models include a constant, a set of year dummies, and a dummy for the fourth month of the wave. Standard errors have been corrected for the presence of multiple observations/person.

Table 7. *Exits from Private Insurance, 1986-1996 SIPP*

	Interrupted Private Insurance Spells		Fresh Private Insurance Spells	
	To Public	To None	To Public	To None
Medicaid/SCHIP eligibility limit	0.003	-0.001	0.004	-0.001
	(0.001)**	(0.000)**	(0.000)**	(0.000)**
Federal and state maximum	-0.011	-0.072	0.207	0.003
EITC credit (/$1000)	(0.109)	(0.048)	(0.096)*	(0.059)
Federal and state EITC initial	-0.038	-0.003	-0.007	-0.011
phase-in rate	(0.020)	(0.008)	(0.015)	(0.010)
Unemployment rate	-0.007	0.041	0.024	0.040
	(0.025)	(0.007)**	(0.021)	(0.010)**
Minimum wage rate	0.210	0.013	0.089	-0.017
	(0.082)*	(0.029)	(0.053)	(0.031)
Medicare expenditures	-0.012	0.012	-0.014	0.026
per enrollee (/$1000)	(0.050)	(0.017)	(0.038)	(0.021)
Age	-0.042	-0.008	-0.040	-0.003
	(0.007)**	(0.003)**	(0.007)**	(0.003)
Male	0.009	-0.021	0.129	0.036
	(0.053)	(0.018)	(0.049)**	(0.025)
Black	0.636	0.317	0.582	0.155
	(0.066)**	(0.027)**	(0.059)**	(0.034)**
Other race	0.556	0.434	0.236	0.283
	(0.126)**	(0.044)**	(0.124)	(0.057)**
Hispanic	0.286	0.256	0.035	0.308
	(0.079)**	(0.031)**	(0.075)	(0.036)**
Family has single female head	1.522	0.924	0.991	0.286
	(0.061)**	(0.023)**	(0.054)**	(0.029)**
Family has single male head	0.910	0.899	0.426	0.513
	(0.136)**	(0.043)**	(0.127)**	(0.061)**
Number of children in family	0.231	0.043	0.103	-0.032
	(0.024)**	(0.010)**	(0.021)**	(0.011)**
Family head's education	-0.244	-0.150	-0.138	-0.079
	(0.009)**	(0.004)**	(0.010)**	(0.005)**
Family head disabled	0.829	0.333	0.722	0.119
	(0.072)**	(0.028)**	(0.063)**	(0.037)**
Age of family head	-0.050	-0.021	-0.027	0.002
	(0.005)**	(0.002)**	(0.004)**	(0.002)
Duration (months)	-0.028	-0.009	-0.110	-0.057
	(0.003)**	(0.001)**	(0.005)**	(0.002)**
Observations	2001530	2001530	250400	250400

Robust standard errors in parentheses (* significant at 5%; ** significant at 1%)
In addition to the variables shown, all models include a constant, a set of year dummies, and a dummy for the fourth month of the wave. Standard errors have been corrected for the presence of multiple observations/person.