Dynamic Opting-in Incentives in Income-tested Social Programs: Evidence from Medicaid/CHIP*

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Abstract

Conventional studies of labor supply in the presence of income-tested social programs implicitly assume that income eligibility for program participation is constantly monitored by the government. However, this is not how most of these programs operate in practice, and the time until the next eligibility recertification can be as long as a year. In particular, the Balanced Budget Act of 1997 gives states the option of insuring children in their Medicaid/CHIP program continuously for up to 12 months regardless of changes in family income. The long recertification period in effect increases the size of the benefit notch, and neoclassical labor supply models predict that agents may lower their labor supply before the application month to gain program eligibility and then increase their labor supply until the next eligibility check. I use the 2001 and 2004 panels of Survey of Income and Program Participation (SIPP) to empirically examine the income and labor supply responses of parents whose children are publicly insured. Comparing theoretical predictions and the empirical evidence points to little labor supply response. Given the absence of strategic behavior, I propose a simple framework to compute the optimal length of the continuous eligibility period relying on the mechanical properties of the income processes observed in SIPP, and derive a mapping from the recertification cost parameters to the optimal monitoring frequencies.

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1 Introduction

An implicit assumption in labor supply studies of income-tested social programs is that program eligibility is being constantly monitored. However, this is not how these programs operate in reality and the time between two consecutive eligibility certifications can be as long as a year. Although this fact is recognized in several studies of program participation,[1] a formal investigation has not been carried out to address how program participants adjust their labor supply behavior in response to the dynamic incentives created by the lack of constant income monitoring. In this paper, I attempt to fill this gap by examining families' behavioral responses to the continuous eligibility provision for children participating in Medicaid and the State Children's Health Insurance Program (SCHIP or simply CHIP). In addition, the positive analysis of labor supply responses can inform the normative question of often the government should check program eligibility, which I also address in this study.

The income testing in transfer programs reflects the government's redistributive taste, and continued eligibility monitoring ensures that the program is targeting the needy. However, if monitoring is costly and incomes of program participants change little over time, it may be sensible for the government to decrease the frequency of eligibility checks and offer a period of "continuous eligibility." From the participants' point of view, there are two channels through which a transfer program becomes more valuable when a period of continuous eligibility is granted. First, transaction costs associated with benefit renewal decrease with fewer renewal periods as pointed out by Currie and Grogger (2001) and Kabbani and Wilde (2003). The second and rarely considered point is that the guarantee of continuous eligibility effectively changes a participant's budget constraint. If the budget constraint non-linearity created by the eligibility requirements distorts a family's labor supply choice, the distortion is eliminated in any period in which eligibility is not checked, allowing the family a more optimal consumption bundle. Increasing the recertification period effectively decreases the number of periods that a family will face the more stringent budget constraint, creating strong incentives for an otherwise ineligible family to opt into the program. That is, families may be induced to temporarily lower their income, gain program eligibility, and revert back to their "optimal" consumption bundle after having acquired the government benefit for the entire continuous eligibility period. As a result,

[1] In the context of Food Stamp, for example, Kornfeld (2002), Currie and Grogger (2001) and Kabbani and Wilde (2003) find that shortening the recertification period reduces the participation rate. Currie and Gahvari (2008) and Currie (2004) both recognize long recertification periods in transfer programs in general, and the latter notes that The Special Supplemental Nutrition Program for Women, Infants and Children (WIC) has a fixed recertification time during which families are eligible for benefits irrespective of income changes.

the lengthening of the recertification period may *create* movements in the income process through labor supply around eligibility checks.

On the one hand, as the length of the continuous eligibility period increases, more families may be expected to participate in the program, resulting in increased expenditure and budget pressure for the government. In addition, these newly participating families of higher income are arguably not the intended beneficiaries of the government transfer. On the other hand, if the continuous eligibility period is significantly shortened, the transaction costs of frequent eligibility recertifications may become insurmountable for a part of the low-income group most in need of the transfer (e.g., single parent families–see Currie and Grogger (2001)). In the case of health insurance, studies (e.g., Olson et al. (2005)) have shown that children who experience interruptions in health insurance coverage are more likely to have unmet health care needs, and therefore imposing large transaction costs on otherwise eligible families is socially suboptimal.[2] Furthermore, verifying eligibility in short intervals leads to increases in administrative cost for the government as well.

Given the tradeoffs of increasing the continuous eligibility period, understanding the behavioral reaction of economic agents to the lack of monitoring has important policy implications. If extensive strategic dip-and-rebound behavior in income is found, then it suggests that the recertification period may be too long. If no strategic behavior is found, on the other hand, labor supply responses to the continuous eligibility provision can be ruled out, and I can compute the optimal eligibility recertification period based on the *mechanical* properties of the empirical income processes. The framework I propose or variants thereof may be applied to study the optimal eligibility recertification frequency under the recent Affordable Care Act–for example, the Medicaid expansion to cover families under 133% of the Federal Poverty Line elicits the question of how often family incomes may need to be verified but its answer is not provided with the Act.

In this paper, I carry out an empirical investigation of the effect and optimality of the continuous eligibility provisions in the context of Medicaid/CHIP. Along with creating the SCHIP program, the Balanced Budget Act of 1997 gave states the option of continuously insuring children for up to 12 months in their public insurance programs regardless of changes in family income during that period. As a result, a third of the states implemented the continuous eligibility option in their public insurance program for children. These states present an opportunity to gauge the significance of the strategic behavior, which sheds light on the choice of the optimal continuous eligibility period.

[2] This is in contrast to the argument in Nichols and Zeckhauser (1982), and is further discussed in section (7).

The contributions of this paper are three-fold. First, I recognize the potential dynamic impact of a long continuous eligibility or recertification period on the labor supply decisions of program participants. I derive qualitative and quantitative predictions of the family income process using neo-classical labor supply models that incorporate the budget constraint relevant for continuous eligibility. Second, I empirically examine the model predictions using data from the Survey of Income and Program Participation (SIPP). Third, I compute the length of the optimal continuous eligibility period under a simple social welfare specification.

Empirically, I find no evidence of the short-term dip-and-rebound strategic behavior in average income as predicted by the neoclassical models for families residing in states that provide 12 months of continuous eligibility, and I statistically reject the model in most subsamples. With labor supply responses practically ruled out, I propose a simple framework to compute the length of the optimal continuous eligibility period using the mechanical properties of the income processes observed in SIPP, and derive a mapping from the recertification cost parameters to the optimal monitoring frequencies. Under moderate costs to both the government and the participate, the calculation suggests that the optimal recertification period may be no shorter than 12 months. Therefore, it may be beneficial for states that still provide a 6-month renewal period, namely Georgia and Texas, to consider halving the renewal frequency; it may also be beneficial for those currently offering 12 months of continuous eligibility not to switch back to a 6-month period as in the case of–for example–Connecticut, Indiana, Nebraska, Washington and New Mexico in the early 2000's.

The remainder of the paper is organized as follows. Section (2) provides an overview of the Medicaid/CHIP institutions. Section (3) presents a series of models to illustrate the tradeoff in a continuous eligibility provision and to theoretically analyze families' responses to such a provision. Section (4) describes data used, and empirical results are presented in Section (5). Section (6) calibrates the labor supply model and compares the quantitative prediction to the empirical results. Section (7) conducts a simulation exercise to obtain the optimal choice of the continuous eligibility period length. Section (8) concludes.

2 Institutional Background of Medicaid and CHIP

The Medicaid program was created by the Social Security Amendments of 1965 and provides health insurance to low-income populations. The program originally targeted those traditionally eligible for welfare–single-parent families, and the aged, blind and disabled. However, eligibility for public insurance through Medicaid, and later, through SCHIP, has expanded substantially over time particularly for the population of dependent children.

Over the 1980s, the link between Medicaid and welfare for children was gradually severed through a series of legislative acts. In 1984, the Deficit Reduction Act required states to cover children less than five years old born after September 30, 1983 living in families income-eligible for Aid to Families with Dependent Children (AFDC), regardless of family structure. Further decoupling occurred with passage of the Omnibus Budget Reconciliation Acts (OBRA) of 1986 and 1987, which allowed states to raise the income limits for Medicaid eligibility above the AFDC thresholds. OBRA 1987 also required states to cover all children less than seven years old born after September 30, 1983 living in families with incomes below the AFDC income threshold. Pregnant women and infants living in families with incomes below 75% of the federal poverty level (FPL) were granted mandatory eligibility through the Medicare Catastrophic Coverage Act of 1988. Also in 1988, the passage of the Family Support Act required states to continue Medicaid coverage for up to one year for families who lost AFDC benefits due to increased earnings.

The two largest federal expansions were included in OBRA 1989 and OBRA 1990, which became effective in April 1990 and July 1991 respectively. OBRA 1989 required states to offer Medicaid coverage to pregnant women and children up to age six with family incomes below 133% of the FPL. OBRA 1990 required states to cover children born after September 30, 1983 with family incomes below 100% of the FPL. The two expansions remain the mandated minimum federal standards for children today: a child under the age 6 is eligible for Medicaid if her family income is below 133% of the FPL, and a child between the age of 6 and 18 is eligible if her family income is below 100% of the FPL (for a detailed account of the major Medicaid legislations by 1997, see Gruber (2003)).

While states are required to adhere to these minimum federal standards from OBRA 1990, the creation of the State Children's Health Insurance Program (SCHIP) in 1997 allowed many states to further expand their public insurance programs above these standards. Unlike Medicaid, SCHIP provided states with block grants to fund coverage for children and left the implementation of program up to the individual states, subject to some rules to prevent crowd out of private insurance and to meet federal benefit standards. Specifically, states could choose to use their funds by expanding their existing Medicaid program, creating a separate program for children who do not qualify for the existing Medicaid program, or a combination of both. In some separate state programs, families who exceed a certain income level were also required to pay a premium for coverage. As a result of the block granting structure of SCHIP, states varied widely in their implementation of public insurance for children. One particular feature of some state programs is a continuous eligibility period as permitted by the Balanced Budget Act of 1997, which provides children with uninterrupted coverage for up to 12 months after confirming eligibility, regardless of whether their families' incomes rise above the eligibility requirement during this period. The focus of this paper is the effect of this continuous eligibility period on public insurance coverage for children and on the labor supply of their families.

In practice, Medicaid and CHIP eligibility is established based on the most recent monthly income, and official income proof[3] needs to be submitted with the application in most cases. However, with the implementation of a continuous eligibility period, some states explicitly mandate that once a family is qualified for coverage, they are eligible for coverage for a fixed, continuous period after that point. After this period, the family is once again required to confirm their eligibility, either by reporting any changes in income, or by actually sending proof of income with a renewal application. Families typically receive a package containing renewal materials 60 to 90 days prior to the expiration of their benefits.

Finally, along with the continuous eligibility provision, the Balanced Budget Act of 1997 also gave states the option of allowing presumptive eligibility for children. That is, states may allow children who appear eligible to obtain temporary Medicaid/CHIP eligibility (so that they may immediately access health care services) while their eligibility based on income is being confirmed.[4] Since children who are covered under presumptive eligibility do not always need to meet the usual income requirements, I analyze the effect of the continuous eligibility provision on family income both including and excluding families in states that provide presumptive eligibility. Twelve states provided presumptive eligibility to children in my sample and are listed in the Appendix.

3 Theoretical Framework of Eligibility Recertification in Transfer Programs

The income or means testing in transfer programs reflects the government's redistributive taste and its intention in targeting the needy. If income does not change over time and those in need remain in need, then there is no point in monitoring program eligibility once families are allowed in the program. Therefore, the necessity of eligibility recertification stems from the possibility that a family having entered the program with

[3]On the current application form for New York State, for example, it states that an applicant must provide a letter,written statement, or copy of check or stubs, from the employer, person or agency providing the income... [the applicant should] [p]rovide the most recent proof of income before taxes and any other deductions. The proof must be dated, include the employee's name and show gross income for the pay period. The proof must be for the last four weeks, whether you get paid weekly, bi-weekly, or monthly. It is important that these be current."

[4]Presumptive eligibility to infants and pregnant women was granted a decade earlier by OBRA '86.

a low income is no longer in need following a large positive income change. From the perspective of the government, this family should be taken off the program roster based on an income eligibility recertification so as to alleviate the pressure on the government's budget. If monitoring eligibility is costless for both the government and family, then the government should perform an eligibility check every period to ensure that the transfer targets the needy as is shown formally below. When there is a cost to eligibility monitoring, the choice of the length of the recertification period in part reflects the compromise between incurring this cost and transferring benefits to those who are not the neediest.

It may be tempting to allow a long continuous eligibility period in the case of high administrative cost or low income volatility, but policy makers should be wary of the potentially large labor supply distortions that result. In the extreme scenario mentioned above where the continuous eligibility period is infinite–once eligible due to a low monthly income, families can claim program benefits for a life-time–the vast majority of the families may decide to temporarily lower their income and participate in the program, which will render the system unsustainable. Therefore, understanding families' income and labor response to the dynamic opt-in incentive is key in the consideration of the optimal continuous eligibility period. In subsection (3.1) I first review the prediction of a class of standard static (i.e., assuming constant eligibility monitoring) neo-classical labor supply models in the presence of an in-kind transfer, and I show in subsection (3.2) that the dynamic problem with continuous eligibility provisions can be reduced to two static problems with different budget constraints. The solution to these problems predicts a dip and rebound in average income at each eligibility check.

3.1 Transfer Program and Labor Supply: Static Models

In this subsection, I analyze the labor supply decisions when eligibility for Medicaid/CHIP is recertified every period. That is, families are eligible for benefits only if their income is below a cutoff as is assumed in the conventional labor supply framework in the literature. The analysis is standard, and implications–at least the qualitative ones–have been explored in other studies (e.g., Blank (1989) and Yelowitz (1995)). I review it here using the utility functional form from Saez (2010) because results derived below will be relevant for the dynamic problem with continuous eligibility provision in section (3.2). Subsection (3.1.2) discusses several extensions of the baseline model: it explores the implication of allowing agents only discrete labor supply choices and the consequences of introducing welfare stigma, income effects and incorporating heterogeneity in the elasticity of labor supply.

3.1.1 Baseline Labor Supply Model

The utility functional form of the baseline model is taken from Saez (2010), who studies the bunching behavior of economic agents in response to non-linearities in the tax schedule. The particular utility functional form has also been used in other recent papers, e.g., Chetty et al. (2011), that study the response to nonlinearities in the budget constraint.

Agents choose *continuous* pre-tax income Z and post-tax income (consumption) C to maximize utility that increases in C and decreases in Z. The implicit assumption is that Z is an increasing function of labor supply, and it is equivalent to formulating the utility function in terms of C and hours worked H as noted below. Specifically, the utility function is of quasi-linear form

$$u(C,Z) = C - \frac{n}{1+1/e}\left(\frac{Z}{n}\right)^{1+1/e} \tag{1}$$

where n and e are parameters indicating taste for work and the responsiveness of pre-tax income to a change in tax rate. Solving the optimization problem implies that an agent chooses optimal pre-tax income $Z^* = n(1-t)^e$ when facing the budget constraint $C = (1-t)Z$. As pointed out by Saez (2010), $Z^* = n$ when $t = 0$, and n can be interpreted as the choice of potential income in the absence of tax and transfer programs. An agent with a larger n both works and consumes more, and n is assumed to be smoothly distributed according to density f_n across the population.

The parameter e is the elasticity of pre-tax income with respect to (one minus) the marginal tax rate because of the following identity $\frac{(1-t)}{(Z^*)}\frac{d(Z^*)}{d(1-t)} = e$. Note that if the utility function is written in terms of consumption and hours worked $u(C,H) = C - \frac{n}{1+1/e}(\frac{wH}{n})^{1+1/e}$ for an agent with taste n and wage rate w, it is also true that $\frac{(1-t)}{(H^*)}\frac{d(H^*)}{d(1-t)} = e$. Therefore I will refer to e interchangeably as the income elasticity or the labor supply elasticity in the subsequent sections of this paper. As is well known, the quasi-linear utility functional form implies no income effects, so e is both the compensated and uncompensated elasticity (in fact, e is also the Frisch elasticity of income/labor supply). I assume e to be constant in this section but the consequence of allowing heterogeneity in e, as well as that of allowing income effects, will be discussed in section (3.1.2).

The presence of Medicaid/CHIP induces at least one discontinuity in the relationship between consumption and income. For simplicity of exposition, however, I include only one such notch and a single marginal tax rate in the presentation in this section.[5] When eligibility is checked every month, this budget constraint can be thought of as being static. Following the "notch" specification adopted by Blank (1989) and Yelowitz (1995) with no saving or borrowing, the budget constraint is

$$C = [Z(1-t)+g]1_{[Z \leqslant \gamma]} + Z(1-t)1_{\{Z>\gamma\}} \tag{2}$$

where γ is the Medicaid/CHIP eligibility cutoff, g the monthly value of public insurance and t the marginal tax rate. As pointed out by, for example Blinder and Rosen (1985), Blank (1989) and Kleven and Waseem (2011), no family will choose income to be just above the threshold. This is intuitive because a family consumes more and works less by choosing its income to be at the eligibility cutoff rather than just above it. Certain families who would have chosen $Z > \gamma$ in the absence of Medicaid/CHIP would now switch to γ. Solving the optimization problem predicts the choice of Z^* for a family of type n:

$$Z^* = \begin{cases} n(1-t)^e & \text{if } n \leqslant n_\gamma \text{ or } n > \bar{n} \\ \gamma & \text{if } n \in (n_\gamma, \bar{n}) \end{cases}$$

where $n_\gamma = \frac{\gamma}{(1-t)^e}$ is the type of agent who would choose income at γ in the absence of the notch and $\bar{n}$ is the highest type of agent who would bunch at γ in the presence of the notch. Figure 1 provides an illustration: an agent with $\bar{n}$ is indifferent between the consumption-income bundle at the notch $(\gamma(1-t)+g, \gamma)$ and her optimal choice in the absence of the notch $(\bar{n}(1-t)^{1+e}, \bar{n}(1-t)^e)$. Therefore, $\bar{n}$ is the solution to the equation

$$\gamma(1-t)+g-\frac{\bar{n}}{1+1/e}(\frac{\gamma}{\bar{n}})^{1+1/e} = \bar{n}(1-t)^{1+e} - \frac{\bar{n}}{1+1/e}(1-t)^{1+e} \tag{3}$$

It follows that the distribution of pre-tax income Z is given by:

$$f_Z(z) = \begin{cases} \frac{1}{(1-t)^e} f_n(\frac{z}{(1-t)^e}) & \text{if z<}\gamma \text{ and } z \geqslant \bar{n}(1-t)^e \\ 0 & \text{if } z \in (\gamma, \bar{n}(1-t)^e) \end{cases}$$

[5] As mentioned in section (2), families enrolled in CHIP with income above the 150% FPL may be subject to moderate premiums and co-payments, which implies a lower CHIP notch than that of Medicaid. The empirical impacts of presence of other notches (induced by Medicaid or other transfer programs) and differential tax rates will be discussed in section (6).

and

$$\Pr(Z = \gamma) = F_n(\bar{n}) - F_n(n_\gamma)$$

In summary, the standard static model makes the prediction that, when a benefit notch is introduced, agents originally choosing income just above the eligibility cutoff will lower their labor supply to locate at the cutoff and become just eligible for benefit. Thus, there is income bunching at the eligibility cutoff and a drop in density to 0 right above the cutoff.

3.1.2 Extensions of the Baseline Model: Discrete Labor Supply Choices, Heterogeneous Elasticity, Welfare Stigma and Income Effects

In the previous subsection (3.1.1), the income/labor supply choice is assumed to be continuous, the income/labor supply elasticity e is held constant across agents, perfect compliance (i.e. those eligible will participate in Medicaid/CHIP) is assumed, and there are no income effects in the utility function (1). This subsection investigates the implication of relaxing these assumptions and shows that the qualitative predictions in the previous subsections still hold true.

Discrete Labor Supply Choices In the preceding subsection, agents' pre-tax income choice is assumed to be continuous which implies that agents are free to choose their hours and hence perfectly control their income. Obviously, this may not be a realistic restriction per Ashenfelter (1980), Ham (1982), Kahn and Lang (1991), Altonji and Paxson (1992), Dickens and Lundberg (1993) and Chetty et al. (2011). In this subsection, I will first derive the theoretical prediction only allowing an agent finitely many hours choices.[6] The main implication is still that certain agents will lower their labor supply in order to claim benefit when a notch is introduced. But rather than bunching at the eligibility cutoff, there is only a discontinuous drop in the density of income at the cutoff.

Because of the discrete labor supply restriction, Z in this section is written explicitly as wH where w is considered to be distributed smoothly among agents. For exposition purposes, I discuss only the case when H can only vary along the extensive margin; that is, an agent can only work full time or not work at all. The general case where H is allowed more than two choices is explored in the Appendix. Let $H = 0$, $H = 1$ denote the labor supply choice of not working and working full time respectively. If workers are constrained

[6] The working paper versions of Saez (2010), Saez (1999) and Saez (2002), address this extension in their simulation section but do not discuss the predictions from a theoretical perspective.

to only these two labor supply options, then the maximization problem becomes $\max_{H\in\{0,1\}} u(C,wH)$ subject to the budget constraint (2) where Z is replaced by wH, and we solve the maximization problem by considering the following two scenarios.

1. $w \leqslant \gamma$. An agent with potential monthly wage below the cutoff can claim benefits whether she works or not. In other words, the budget constraint she faces is only the segment to the left of γ: $C = (1-t)wH + g$. Consequently, maximizing utility involves the comparison of $u(g,0)$ and $u((1-t)w+g,1)$. To characterize the solutions, consider the agent of type $\bar{n}^l$ who is indifferent between choosing $H=0$ and $H=1$ at wage w.[7] Therefore, $\bar{n}^l$ solves

$$u(g,0) \equiv g = (1-t)w + g - \frac{n}{1+1/e}(\frac{w}{n})^{1+1/e} \equiv u((1-t)w+g,1)$$

which implies that $\bar{n}^l(w) = (\frac{w^{1+1/e}}{[(1-t)w](1+1/e)})^e$. Since $\frac{n}{1+1/e}(\frac{w}{n})^{1+1/e}$ is decreasing in n (i.e. the disutility of working is less for an agent with high n), agents with wage w and of type $n \geqslant \bar{n}^l(w)$ choose $H=1$ and those with $n < \bar{n}^l(w)$ choose $H=0$.

2. $w > \gamma$. An agent with potential monthly wage above the cutoff is eligible for benefits only if she chooses not to work. The type of agent who is indifferent between working and not working at wage w equates $u(g,0)$ and $u((1-t)w,1)$. Because her type $\bar{n}^r$ solves

$$u(g,0) \equiv g = (1-t)w - \frac{n}{1+1/e}(\frac{w}{n})^{1+1/e} \equiv u((1-t)w,1)$$

$\bar{n}^r(w) = (\frac{w^{1+1/e}}{[(1-t)w-g](1+1/e)})^e$.[8] Analogous to the case above, agents with $n \geqslant \bar{n}^r(w)$ choose to work full time while those with $n < \bar{n}^r(w)$ choose not to work.

To summarize, if $\bar{n}_{0,1}$ denotes the type of agents who are indifferent between working and not working, then

$$\bar{n}_{0,1}(w) = \begin{cases} \bar{n}^l(w) & \text{if } w \leqslant \gamma \\ \bar{n}^r(w) & \text{if } w > \gamma \end{cases}$$

$\bar{n}_{0,1}$ varies smoothly with w within each case, but there is a discontinuous increase in $\bar{n}_{0,1}$ as w crosses γ. When w and n follow a smooth joint distribution $f_{n,w}$ over the first quadrant of $\mathbb{R}^2$, this discontinuous drop

[7] The superscript l here stands for left as w lies to the left of γ. The superscript r will be used in the next case.

[8] Note that a positive n^r exists–n^r has to be positive for the marginal utility of work to be negative–when $(1-t)w > g$, which means that the post-tax income of working full time at wage w is larger than the value of benefit g. This is most likely satisfied in reality for families with a wage above the CHIP cutoff.

in threshold agent type implies no bunching but a discontinuity in the density of pre-tax income $Z = wH$ at γ. To see this, notice that the c.d.f of Z evaluated at $z > 0$ is

$$F_Z(z) = \Pr(Z=0) + \Pr(0 < Z \leqslant z) = \Pr(H=0) + \Pr(H=1, w \leqslant z) \tag{4}$$

On two sides of the eligibility cutoff γ, the values of F_Z are

$$\begin{aligned} F_Z(z) &= \begin{cases} \Pr(H=0) + \Pr(w \leqslant z, n \geqslant \bar{n}^l(w)) & \text{if } z \leqslant \gamma \\ \Pr(H=0) + \Pr(w \leqslant \gamma, n \geqslant \bar{n}^l(w)) + \Pr(\gamma < w \leqslant z, n \geqslant \bar{n}^r(w)) & \text{if } z > \gamma \end{cases} \\ &= \begin{cases} \Pr(H=0) + \int_0^z \int_{\bar{n}^l(w')}^{\infty} f_{n,w}(n',w')dn'dw' & \text{if } z \leqslant \gamma \\ \Pr(H=0) + \int_0^\gamma \int_{\bar{n}^l(w')}^{\infty} f_{n,w}(n',w')dn'dw' + \int_\gamma^z \int_{\bar{n}^r(w')}^{\infty} f_{n,w}(n',w')dn'dw' & \text{if } z > \gamma \end{cases} \end{aligned}$$

Since $\int_0^z \int_{\bar{n}_l(w')}^{\infty} f_{n,w}(n',w')dn'dw'$ is continuous in z and $\lim_{z\downarrow\gamma} \int_\gamma^z \int_{\bar{n}^r(w')}^{\infty} f_{n,w}(n',w')dn'dw' = 0$, $F_Z(z)$ is continuous at γ. Hence, there is no bunching at the eligibility cutoff unlike in section (3.1.1) where agents can choose along the intensive margin of labor supply.

However, the p.d.f of Z, $f_Z(z)$, is not continuous at γ. By continuity of $f_{n,w}$, $\bar{n}^l$ and $\bar{n}^r$ along with an application of the Fundamental Theorem of Calculus,

$$\begin{aligned} \lim_{z\uparrow\gamma} f_Z(z) &= \int_{\bar{n}^l(\gamma)}^{\infty} f_{n,w}(n',\gamma)dn' \\ \lim_{z\downarrow\gamma} f_Z(z) &= \int_{\bar{n}^r(\gamma)}^{\infty} f_{n,w}(n',\gamma)dn' \end{aligned}$$

Since $\bar{n}^r(\gamma) > \bar{n}^l(\gamma)$, $\lim_{z\uparrow\gamma} f_Z(z) > \lim_{z\downarrow\gamma} f_Z(z)$ which implies a discontinuous drop in the income density at γ.

The constraint that workers can only work full time or not work at all is too restrictive. In reality, workers may and do work part time. It is plausible that employers offer several hours-of-work choices to their employees. As shown in the Appendix, the result of no bunching but a density discontinuity at the cutoff holds true when H takes on a finite number of values.

Heterogeneous labor supply elasticities Instead of requiring agents to share the same labor supply elasticity, the first part of this subsection studies the pre-tax income distribution when elasticities are heterogeneous across families. In section (3.1.1), the threshold taste parameter–$\bar{n}$–is a function of e, and all statements are true for each $e > 0$. Now suppose that e is heterogeneous and distributed smoothly across agents. In the case where there is no constraint on labor supply, the discontinuous drop in the income density at γ is

$$\lim_{z\uparrow\gamma} f_Z(z) - \lim_{z\downarrow\gamma} f_Z(z) = \int_0^\infty \frac{1}{(1-t)^e} f_{n|e}(n_\gamma(e)|e) f_e(e) de \tag{5}$$

since $\lim_{z\uparrow\gamma} f_Z(z) = \int_0^\infty \frac{1}{(1-t)^e} f_{n|e}(n_\gamma|e) f_e(e) de$ and $\lim_{z\downarrow\gamma} f_Z(z) = 0$, and the fraction of agents bunching at γ is

$$\Pr(Z=\gamma) = \int_0^\infty (F_{n|e}(\bar{n}(e)|e) - F_{n|e}(n_\gamma(e))) f_e(e) de \tag{6}$$

where $\bar{n}(e)$ and $n_\gamma(e)$ are as defined in subsection (3.1.1): $\bar{n}(e)$ is the solution to (3) and $n_\gamma(e) = \frac{\gamma}{(1-t)^e}$. Since the integrands in both (5) and (6) are positive, there is still bunching and a discontinuous drop in the income density at γ. Analogously, the result of no bunching but a density discontinuity at γ presented earlier in this subsection also holds when labor supply is constrained to several choices–since the result holds for all e, it also holds when integrating over the density of e.

Non-participation To account for non-participation among eligible agents, I follow a conventional approach by Moffitt (1983) and introduce welfare stigma. As pointed out in Moffitt (1983), however, the stigma term can also encapsulate more than the simple psychological cost of being perceived as a beneficiary of government programs. For example, it may incorporate the cost of applying for benefit such as filling out the required forms and learning about program rules. The simplest formulation of welfare stigma is a flat cost to participating in welfare programs. The maximization problem becomes:

$$\max_{C,Z,P} u(C,Z) - \phi P$$

where an agent's welfare participation decision $P \in \{0,1\}$ depends on the stigma parameter $\phi > 0$.

In effect, introducing welfare stigma shifts down the program segment of the budget constraint $[Z(1-t)+g]1_{[Z\leqslant\gamma]}$ by ϕ and therefore reduces the public insurance notch to $\max\{g-\phi,0\}$. If ϕ is constant across agents and $\phi < g$, then all the analyses in (3.1.1) carry through by replacing g with $\tilde{g} = g - \phi$. When ϕ is heterogeneous, the income distribution is smooth for the sub-population with $\tilde{g} = g - \phi \leqslant 0$, and analyses from previous subsections only hold true for those with $\tilde{g} > 0$. In the entire population, the qualitative predictions from (3.1.1) are still valid if (n,e,ϕ) follows a smooth distribution supported on $\mathbb{R}^4_{++}$, although the bunching and density discontinuities are less pronounced due to the existence of non-participants.[9]

Income effects As mentioned in section (3.1.1), the quasi-linear functional form of (1) eliminates income effects. This may be reasonable in the context of a tax rate change (i.e. a kink in the budget constraint), since as Chetty et al. (2011) note, tax rate changes have little effect on average tax rates. In the case of a notch, however, the absence of income effects in modeling may no longer be appropriate. Here I explore the implication of using a functional form that allows non-zero income effects.

Consider the utility function

$$u(C,Z) = \frac{C^{1-\rho}}{1-\rho} - \frac{n}{1+1/e}(\frac{Z}{n})^{1+1/e} \tag{7}$$

which displays constant relative risk aversion in consumption, and which encapsulates the quasi-linear utility (1) as a special case when $\rho = 0$. When facing a budget constraint $C = (1-t)Z$, the optimal interior pre-tax income choice is $Z^* = (1-t)^{\frac{e}{\rho e+1}} n^{\frac{1}{1+\rho e}}$. Therefore, $n^{\frac{1}{1+\rho e}}$ is the agent's desired income choice when $t = 0$. Instead of the Marshallian, Hicksian and the Frisch elasticity all being e as in the quasi-linear case, e for the utility functional form (7) is only interpreted as the Frisch elasticity of income/labor supply, i.e. the elasticity holding marginal utility of wealth constant. This interpretation of e will be convenient for the dynamic problem we consider below. Note that the Marshallian elasticity of labor supply with respect to the marginal tax rate reduces to $\frac{\partial Z^*}{\partial(1-t)} \frac{1-t}{Z^*} = \frac{e}{\rho e+1} < e$ when $\rho > 0$ whereas the Hicksian elasticity varies across agents.[10]

The analyses undertaken in sections (3.1.1) carry through with the more general utility function (7) although the expressions for the various $\bar{n}$'s will change. Therefore, the introduction of non-zero income effects does not change the qualitative predictions. That is, there is income bunching at the eligibility cutoff when agents have prefect control over their income and a discontinuous drop in income density at the cutoff when agents face a menu of finitely many labor supply choices. The intuition is that these predictions hinge on the convexity of the indifference curves, which is not altered when curvature in consumption utility is introduced.

[9]Note that allowing heterogeneity in ϕ is equivalent to allowing heterogeneity in g, but a more general interpretation of the heterogeneity in the notch size is permitted. For example, families with healthier children arguably value health insurance less than those with sicker children and would hence face a larger notch.

[10]See MaCurdy (1981) and Browning et al. (1985) for discussions on the magnitudes of the three elasticities.

3.2 Continuous Eligibility and Labor Supply–Dynamic Models

This section extends the static framework in the previous section to incorporate continuous eligibility provisions. In essence, the provisions allow a more generous budget constraint over time than (2). More specifically, families that are just approved for public insurance can have income above γ and remain covered until the eligibility recertification a year later. To characterize a family's consumption and labor supply decisions in the presence of continuous eligibility provisions, I cast the family's utility maximization problem in a dynamic programming framework.

Formally, the state variable s is the number of months until recertification (s is defined to be 0 for those not claiming benefits since they will face the eligibility check when they apply), and let τ be the number of months of provided continuous eligibility. In each period, an agent chooses whether or not to participate in the program:

$$V_s = \max_{P_s} P_s V_s^1 + (1 - P_s) V_s^0$$

where $P_s = 0, 1$ denotes participation choice, and V_s^1 and V_s^0 are utilities associated with participating and not participating in the program when agents are s months away from an eligibility check. Formally, the expressions for V_s^1 and V_s^0 are

$$V_s^1 = \max_{C,Z} \{u(C,Z) + \beta V_{s'}\}$$

s.t. $Z < \gamma$ if $s = 0$; $C = (1-t)Z + g$

$$s' = \begin{cases} s-1 & \text{if } s > 0 \\ \tau - 1 & \text{if } s = 0 \end{cases}$$

$$V_s^0 = \max_{c,z} \{u(C,Z) + \beta V_{s'}\}$$

s.t. $C = (1-t)Z$

$$s' = \begin{cases} s-1 & \text{if } s > 0 \\ 0 & \text{if } s = 0 \end{cases}$$

For illustration purposes, first consider the simple case when $\tau = 2$, in which case s takes on the value 0 or 1. Let $\{C_s^p, Z_s^p\} = \text{argmax} V_s^p$ for $p = 0, 1$. The dynamic problem is thus simplified to

$$\begin{aligned} V_0 &= \max_{P_0} P_0 \{u(C_0^1, Z_0^1) + \beta V_1\} + (1 - P_0)\{u(C_0^0, Z_0^0) + \beta V_0\} \\ V_1 &= \max_{P_1} P_1 \{u(C_1^1, Z_1^1) + \beta V_0\} + (1 - P_1)\{u(C_1^0, Z_1^0) + \beta V_0\} \end{aligned}$$

and I will characterize the optimal P_s, C_s^p and Z_s^p's below.

First note that choosing $P_1 = 1$ strictly dominates $P_1 = 0$ because (C_1^0, Z_1^0) lies in the interior of the budget set for an agent with $s = 1$. In other words, when benefit can be claimed at no cost (i.e. no restrictions on income), a rational family will do so. This reasoning simplifies the expression for V_1: $V_1 = u(C_1^1, Z_1^1) + \beta V_0$. Plugging in this expression of V_1 into that of V_0 leads to

$$V_0 = \max_{P_0} P_0\{u(C_0^1, Z_0^1) + \beta u(C_1^1, Z_1^1) + \beta^2 V_0\} + (1 - P_0)\{u(C_0^0, Z_0^0) + \beta V_0\}$$

For the agents indifferent between choosing $P_0 = 0$ and $P_0 = 1$,

$$V_0 = u(C_0^1, Z_0^1) + \beta u(C_1^1, Z_1^1) + \beta^2 V_0 = u(C_0^0, Z_0^0) + \beta V_0$$

and therefore $V_0 = \frac{u(C_0^0, Z_0^0)}{1-\beta}$. It follows that

$$u(C_0^1, Z_0^1) + \beta u(C_1^1, Z_1^1) = u(C_0^0, Z_0^0) + \beta u(C_0^0, Z_0^0) \tag{8}$$

If u has the functional form in (1), then $C_1^1 = C_0^0 + g$ and $Z_1^1 = Z_0^0$ because of quasilinearity. Consequently, $u(C_1^1, Z_1^1) = u(C_0^0, Z_0^0) + g$, and (8) leads to

$$u(C_0^1, Z_0^1) + \beta g = u(C_0^0, Z_0^0) \tag{9}$$

Suppose (C_0^1, Z_0^1) satisfying (9) is an interior solution. Then the convex indifference curve passing through the bundle (C_0^1, Z_0^1) is tangent to the program segment of the budget constraint and therefore lies above the non-program budget constraint $C = (1-t)Z$. Consequently, $u(C_0^1, Z_0^1) > u(C_0^0, Z_0^0)$ implying that $u(C_0^1, Z_0^1) + \beta g > u(C_0^0, Z_0^0)$, contradicting (9). Therefore, the (C_0^1, Z_0^1) that satisfies (9) has to be a corner solution with $Z_0^1 = \gamma$. Denote the indifferent agent's type by $\bar{n}^{dynamic}$ and expanding (9) using the quasi-linear functional form leads to

$$\gamma(1-t) + (1+\beta)g - \frac{\bar{n}^{dynamic}}{1+1/e}\left(\frac{\gamma}{\bar{n}^{dynamic}}\right)^{1+1/e} = \bar{n}^{dynamic}(1-t)^{1+e} - \frac{\bar{n}^{dynamic}}{1+1/e}(1-t)^{1+e} \tag{10}$$

Equation (10) states that an agent of type $\bar{n}^{dynamic}$ is indifferent between choosing her interior solution on the budget constraint segment $C = (1-t)Z1_{\{Z>\gamma\}}$ and the post-tax/pre-tax income bundle $(\gamma(1-t) + (1+\beta)g,\ Z)$. Analogous to the analyses in section (3.1.1) and illustrated in the right panel of Figure 1, agents with $n \leqslant \bar{n}^{dynamic}$ choose to participate in the program and those with $n > \bar{n}^{dynamic}$ do not. While those with $n \in (0, n_\gamma]$ participate without altering their labor supply, those with $n \in (n_\gamma, \bar{n}^{dynamic}]$ will lower their labor supply and income when $s = 0$ to gain eligibility but revert back to their desired interior solution with an income above γ when their eligibility is not checked (i.e. $s > 0$). Comparing (10) to (3) reveals that doubling the length of the recertification period in effect doubles the benefit notch if $\beta \approx 1$. It is easy to show that for a general recertification period τ, the size of the benefit notch an agent faces is effectively $\sum_{i=0}^{\tau-1} \beta^\tau g \approx \tau g$ when making her participation decision when $s = 0$.

There are two extensions to consider. First if a cost is associated with applying for benefit, then the marginal agents at period $s = 0$ will compare choosing a notch of size $\tau g - \phi$ to their interior pre-tax income choice on $C = (1-t)Z$ where ϕ entails the application cost. The results above hold for agents whose $\phi < \tau g$. Second, when income effects are take into account, the solution may no longer be obtained analytically. Qualitatively, once a new applicant family is approved for benefit, the transfer may reduce labor supply through the income effect channel. This will imply that the rebound in income after starting a public insurance spell will not be as large as when income effects are absent. In section (6), I will calibrate the model that allows income effects and compare the predicted effect to that observed empirically.

To summarize, the dynamic labor supply models make the prediction that average income drops at the income eligibility check and rebounds afterward though the magnitudes of the dip and rebound depend on factors such as the size of income effects. In the following sections, I will examine whether agents empirically behave as predicted by the labor supply model.

4 Data and the Construction of the Analysis Sample

4.1 Data Sources

To examine the income and labor supply responses to the continuous eligibility provisions in Medicaid/CHIP, I use data from the 2001 and 2004 panels of Survey of Income and Program Participation. SIPP is a representative household survey designed to provide detailed information on incomes and labor force and government program participation. Each of the panel files contains four rotation groups, and they span the period from October 2000 to December 2003 and from October 2003 to December 2007 respectively. All of the rotation groups in the 2001 panel provide information for 36 consecutive months, and those in the 2004 panel for 48 months. Each adult member of the participating household was interviewed every four months about his or her experiences since the last interview (i.e. four-month reference period).

The chief advantage of SIPP over other candidate datasets (CPS, PSID, HIS, etc.) is its panel structure at the monthly frequency and the rich array of variables including detailed information on income, program participation, and family structures. Since the focus of the study is to examine families' income and labor supply behavior before and during their children's Medicaid/CHIP spells, SIPP is the best choice among public use survey data sets for the purpose of this study.

There are, however, several limitations of the data used. First is the existence of the well-known seam bias, which refers to the fact that changes in status are under-reported within a four-month reference period while over-reported between two reference periods (see, for example, Pischke (1995) and Ham et al. (2009) for details). As noted above, the interviews are not conducted every month but every four months, and children's reported public insurance coverage spells are therefore much more likely to start on the first month of the reference period than the second, third or fourth. In fact, about 80% of the fresh spells in the 2001 panel and 90% of the fresh spells in the 2004 panel start on the first month of the reference period. Complications created by the seam bias will be addressed in section (6).

Second, Medicaid and CHIP coverages cannot be reliably distinguished, and this is true with all survey data.[11] Therefore, I will use public insurance coverage which encapsulates both Medicaid and CHIP, and the phrase "public insurance" will be used interchangeably with Medicaid/CHIP or simply Medicaid. When computing the value of the benefit notch, I will use the CHIP government spending per enrollee, which is lower than that of Medicaid. The implication of ignoring the higher benefit notch Medicaid applicants face will be discussed in section (6).

Third, identifiers of families in less populated states are missing from the 2001 panel. Families in Maine and Vermont share the same state identifier as well as those in North Dakota, South Dakota and Wyoming. Because these states have different Medicaid/CHIP policy parameters, they are excluded from analyses. Due to the larger sample size of the 2004 panel, all fifty states plus the District of Columbia have their own identifier, and therefore all states are included.

The main analysis sample consists of children who started a public insurance spell during the SIPP panel. The restriction to those with "fresh" spells (as opposed to the left-truncated spells that start with the

[11] An expert at the U.S. Census Bureau noted in a correspondence that "respondents rarely know with certainty whether their child is in Medicaid or CHIP... We found this out with the 2004 SIPP instrument, where question order happened to be revised so that CHIP was asked about before Medicaid. Here we observed that respondents were most likely to answer the question asked first, resulting in higher reported levels of CHIP than of Medicaid for Panel 2004)."

child's first appearance in the panel) comes from the necessity of identifying when the family applied for benefit, which is not possible with the left-truncated spells. In addition, children younger than the age of 1, children whose families moved to another state during the spell and children who were on the Supplemental Security Income (SSI) program at the beginning of a public insurance spell are excluded from the analysis sample. Infants are excluded because most states have been extending presumptive eligibility to infants since the 1990's; children whose families moved across states pose a challenge in assigning Medicaid/CHIP parameters; and children who are on the SSI program are conferred automatic eligibility for public insurance. As shown in Table 2, the analysis sample consists of–for the 2001 and 2004 panels respectively–7158 and 8321 fresh spells in total and 3096 and 3312 fresh spells from children in the states that offer continuous eligibility.

Nuclear families for each child are constructed using information on the relationship to household and family reference person (head). In cases where a child and his or her parent(s) live with other adults, however, families include only the children and parent(s) of the appropriate subfamily. This definition corresponds to the family assistance unit that would be potentially eligible for Medicaid/CHIP. Family level variables are then calculated by aggregating over individual family members, and family income includes earned and unearned incomes excluding welfare receipts and children's incomes.[12]

The state level Medicaid/CHIP data are extracted from reports issued and databases maintained by various organizations. The policy parameters (e.g., continuous eligibility, presumptive eligibility, income eligibility cutoffs, etc.) come from NGA (2000-2008), Kaiser (2002-2011) and CMS (Various Years). Medicaid/CHIP spending and enrollment data are extracted from the Kaiser Foundation State Health Facts database and the CMS Medicaid Statistical Information Statistics System.

4.2 Adjustment to Potential Measurement Error in Public Insurance Coverage

The accurate identification of a public insurance spell start is important for the empirical analysis in the following sections. In the data, many fresh spells are preceded by a short gap in public insurance coverage. Short coverage gaps are not inconsistent with what is found using administrative data. For example, using administrative data from Ohio, Fairbrother et al. (2011) show that 40% of the children whose coverage was not renewed at month 12 re-enroll within a short period. However, it does cause concern regarding the

[12]The exclusion of children's income is due to the fact that student income is disregarded for the purpose of Medicaid/CHIP eligibility determination. Whether or not other adult family members' incomes are included in the computation of family income in addition to those of the parents makes little difference empirically.

reliability of identifying the start of a spell. Although it is rare for families to report coverage while they are not on public insurance (Card et al. (2004)), under-reporting coverage at a particular month during a long spell will lead to the false identification of starting a fresh spell.

To address this potential measurement error problem, I construct a subsample consisting of children who report no public insurance coverage for 12 consecutive months before the start of a spell. This subsample will be henceforth referred to as the "long gap" sample. As shown in Table 2, the 2001 panel long gap sample includes 501 spells from 501 children in 302 sample units and the 2004 panel long gap sample includes 815 spells from 804 children in 494 sample units. Note that the long gap sample contains mostly single spells by virtue of its construction.

Table 3 presents summary statistics for both the full sample and the long gap sample in the 2001 and 2004 SIPP panels. In the full sample, a child switches onto public insurance during a SIPP panel when she is between 8 and 9 years old on average. About half of the children are female; a quarter are black in the 2001 panel and only 17% in the 2004 panel. The average child lives in a four-person nuclear family, and 40% to 50% come from a single-parent family. The vast majority of the families are working families–only around 10% do not report earnings around the time their child starts a public insurance spell and less than 5% of the parents claim unemployment benefits. Less than 7% of the families in all samples receive welfare cash transfers from TANF programs. Many children report private insurance coverage while on Medicaid/CHIP, and this dual or overlap coverage phenomenon has been observed by other studies. Gruber and Simon (2008) note that there is no clear evidence on the "correct" interpretation of the overlap but state two hypotheses: 1. It could be individuals moving from private to public insurance or 2. CHIP claimants report being on both public and private insurance because it is often delivered by HMOs. Under both hypotheses, I can interpret the switch from no public insurance to public insurance as the start of a public insurance spell, and therefore dual coverage does not pose a threat to the empirical studies that ensue. Finally, only a small fraction of parents switch onto Medicaid with their children.

In comparison, children in the long gap sample come from families in better economic conditions. Fewer children (10 percentage points) come from single-parent families, and family incomes are more than 30% higher as compared to the full sample. In the next section, I will present results for both the full sample and the long gap sample. In either sample, I find little evidence of the predicted strategic dip-and-rebound behavior.

5 Descriptive Analysis of Income and Labor Supply Responses

In the section, I present descriptive evidence on families' income response over their childrens' Medicaid/CHIP spell. I follow a flexible specification adopted by Jacobson et al. (1993). Specifically I estimate

$$y_{it} = \omega_i + \nu_t + \sum_{|k| \geqslant m} D_{it}^k \delta_k + \varepsilon_{it} \tag{11}$$

where ω_i and ν_t are individual and calendar month fixed effects respectively and D_{it}^k is a set of dummy variables indicating months after the start of a public insurance spell.[13] $D_{it}^k = 1$ if child i started her public insurance spell at month $t-k+1$. As a special case, a child with $D_{it}^0 = 1$ started her public insurance spell in month $t+1$, and another child with $D_{it}^1 = 1$ started her spell in month t. Month 0 is the omitted category and the δ_k's measure the difference in the average outcome k months after the start of a spell relative to the value at the beginning of the spell. I examine the income and labor supply responses 24 months before and after the beginning of a spell. Since families were interviewed for 36 months in the 2001 panel and 48 months in the 2004 panel, it is possible to allow $m = 35$ for the 2001 panel and $m = 47$ for the 2004 panel. However, there are few families who start a spell at the second month or the last month of the panel which render the estimation of δ_m and δ_{-m} imprecise for large m. Even though the sample period for $m = 24$ covers two years of data surrounding an additional recertification period ($m = 12$), I will only focus on the initial entry of program participants. The reason is mentioned in Section (2): families receive a package containing renewal materials 60-90 days prior to the end of the 12-month period, which creates ambiguity in the timing of potential strategic behavior at eligibility recertification.

According to the theoretical models in Section (3), the δ_k's are expected to be positive for k not being a multiple of 12 (eligibility check points) if there is strategic behavior. However, even in the absence of any strategic behavior, one might expect a mechanical dip as pointed out by Ashenfelter (1978) and Ashenfelter and Card (1985). For example, if selecting into public insurance is based on $y_{i(t_0-k)} < \bar{y}$ where t_0 is the month of starting the spell and that the ε_{it}'s are serially correlated, then a dip and rebound may be expected based purely on mean reversion, though not as abrupt as predicted by the strategic behavior. Given the existence of the mean-reversion mechanism, the dip and rebound due to the strategic behavior should be more pronounced.

[13] Inclusion of time-varying covariates such as state monthly unemployment rate changes the empirical results little.

Note that many families in states that provide 12-months of continuous eligibility do not report coverage for all 12 months after beginning the spell. Likewise, many families only experience short gaps leading up to the beginning of a public insurance spell. This makes it difficult to interpret the δ_k's in an event-study framework, which usually calls for single status transitions. Therefore, I will truncate the analysis sample for each child and focus on the single transitions. Specifically, let k^+ denote the first month after month 0 the child switches off public insurance, and let k^- denote the last month before month 0 the child was covered by public insurance. I will discard all observations after k^+ and those before k^-.

Figure (2) and Figure (3) plot the movement of (unweighted) average family income over the 24 periods around the beginning of a public insurance spell. Both point estimates and standard errors are shown, where the standard errors are clustered at the sample unit level. None of the figures show a pronounced dip-and-rebound in the six months before and after the spell start. For the 2001 Panel, the income trend leading up to the beginning of spell is flat in both samples, however, the 95% confidence interval does not rule out a downward trend. For the full sample specification, the income increases gradually especially after 12 months, but the period immediately following the spell start shows no rebound. Even the upward income trend between 12 months and 24 months after the spell is not statistically different from zero, and it disappears altogether when restricting to the long gap sample in Figure (3). In the 2004 panel, the income process shows a persistent downward trend in both samples, and the estimates of δ_k are significantly positive for many $k < 0$ and negative for many $k > 0$.

Unfortunately, SIPP does not collect information on hours worked on a monthly level but usual hours worked are reported for the entire wave. If the labor supply models presented above are true and imply only supply movements immediately before and after a public insurance spell, then using the usual hours worked variable may cloud the dip-and-rebound pattern. Instead, I describe the movement of the less refined labor supply variables at the monthly level before and after the start of a public insurance spell. In particular, I construct a dummy variable indicating whether or not the head of the family–defined to be father in a two-parent family and all single-parent family heads–worked more than 35 hours for all weeks during a month, and plot its movement in Figure (4) and Figure (3) for the full sample and long gap sample respectively. In all figures, there is a slight downward trend for the two years before the spell start, and it continues in the 2001 panel for at least 6 months in both samples. The trend flattens after the insurance spell in the full sample of the 2004 panel, but the downward trend continues as with the 2001 panel when I restrict to the long gap sample.

Even though the strategic behavior is not visible for the full and long gap sample, the question remains whether income responses are pronounced for a particular subgroup, which may not be detected when averaging with others. I present income responses for four subgroups that may be more likely to respond to the dynamic opt-in incentive. The four subgroups are: (1) children in two-parent families during the sample period, (2) children whose parents worked in the construction industry during the sample period, (3) children whose mother is college educated and (4) children in states offering no presumptive eligibility to non-infants. Two-parent families may be less credit constrained and have more flexibility in adjusting labor supply; many jobs in the construction industry are of seasonal nature and parents may time their government benefit application when they do not work; highly educated parent(s) may be more likely to understand program rules; and parents in states that do not offer presumptive eligibility (see section (2) for definition) will need to have their income low enough so that their children can acquire public health insurance. Figures (6), (7), (8) and (9) plot the income responses for the four subgroups respectively. Contrary to expectation, they do not show the apparent dip-and-rebound pattern. In fact, the trends are fairly similar to those observed in the full sample.

In summary, both the labor supply theory and mechanical mean reversion predict a dip-and-rebound in family income and labor supply around the start of a public insurance spell. However, I do not find such patterns using the various subsamples of the SIPP 2001 and 2004 panel. In some cases, the average incomes are significantly below that of month 0, but small sample size leads to a 95% confidence interval whose upper bound is positive. Therefore, strategic behavior cannot be strictly ruled out. In the next section, I present results from calibrating the labor supply models using various elasticity measures and test whether the empirical estimates are consistent with the quantitative theoretical predictions.

6 Calibration

In this section, I provide quantitative predictions by calibrating the simple models presented in section (3). Specifically, I focus on the dynamic model where the labor supply choice is continuous and the flow utility is of the form (3.1) and (7) and attempt to find the labor supply elasticity parameter that is consistent with the empirical evidence. The case where labor supply choices are discrete is currently being investigated and will be included in a future version of the paper.

For the calibration exercise, I generate 100,000 families for whom I assign the taste parameter n, income eligibility cutoff γ, size of the benefit notch as well as the tax rate t. The distribution of n is non-parametrically estimated using the family income distribution from SIPP data. In particular, recall that the optimal pretax income choice for a family with quasi-linear utility and taste parameter n facing the budget constraint $C = (1-t)Z$ is $Z^* = (1-t)^e n$. For each family in SIPP, I assign the marginal federal income tax rate based on their income and family composition.[14] Using families with children residing in states that offer continuous eligibility, I impute their value of n as $Z^*/(1-t)^e$ where Z^* is family income and estimate the distribution of n using a kernel density estimator for each e as in Brewer et al. (2010). In the case where the flow utility is of the form (7), $n = \frac{Z^*}{(1-t)^e}[(1-t)Z^*]^{\rho e}$.

In this section, I consider only the CHIP benefit notch, which is the notch at the highest public insurance eligibility cutoff. The CHIP notch is smaller than that of Medicaid as most states demand no premium payment for Medicaid and lower or no copay.[15] Ignoring the larger Medicaid notch will bias downward the theoretical prediction of the size of dip and rebound as discussed below. An estimate of the benefit notch value g comes from the CHIP spending data collected by the Kaiser Foundation and the Center for Medicare and Medicaid Services. The spending variable excludes beneficiary and third-party payment and should reflect expected government subsidy. Unfortunately, state-by-state spending per child enrollee figures are not readily available from either source for years earlier than 2004. Therefore, I use the average per-enrollee-spending for the entire U.S. as a measure of the notch, which had increased from \$835 in 2001 to \$1217 in 2007 in nominal terms (approximately 5% annual growth rate). The monthly benefit amount per child g is $\frac{1}{12}$ of the annual spending per-enrollee spending, and the size of the notch a family faces is g times the number of children they have. The marginal distribution of the number of children in each family in the simulation sample mimics that in SIPP–approximately 32%, 37% and 21% of families have 1, 2 and 3 children in both the 2001 and 2004 panels of SIPP. Finally, the CHIP income eligibility cutoff γ is the average of the cutoffs families face in continuous eligibility states in SIPP sample.

I show calibration results by using two models–1. the quasi-linear model, i.e. $\rho = 0$ and 2. the model with $\rho = 0.74$, which is the average value of ρ from empirical literature as surveyed by Chetty (2006). As expected, when income effects are taken into account, the magnitudes of the dip and the rebound are smaller as the increase/decrease in income render agents demand more/less leisure. Also, the rebound is smaller

[14] Specifically, I assume that parents in a dual-headed family file jointly and claim the deduction accordingly and that all families claim standard deductions.

[15] According to the Kaiser Family Foundation, the annual per child government spending in Medicaid and CHIP are \$2171 and \$1363, respectively, for the 2008 fiscal year.

in magnitude than the dip, reflecting the demand for more leisure as children in families acquire public insurance.

Calibration results from the SIPP 2001 and 2004 panels are presented in Table 4 and Table 5 respectively as well as in Figure10. I compare model predicted income responses based on e=0.15[16], e=0.05 and e=0 to those observed empirically, and model predictions are compared to both the empirical point estimates and the upper end points of the 95% confidence intervals to account for sampling errors. Even the smallest model predicted rebound responses, which are based on $e = 0$, are larger than the upper end points of the 95% confidence interval, except for month 10 in the long gap sample of the 2004 panel.[17] The comparison therefore points to little labor supply response.

Note that the theoretical prediction of dip and rebound magnitudes may still be an underestimate for two reasons. First, as pointed out previously, the existence of the Ashenfelter dip should accentuate the dip and rebound. Second, because of the high income cutoff of CHIP, there are many programs agents eligible for CHIP may qualify for if they reduce their income. For example, even though a five-year-old child in a family with income at 140% of the FPL is eligible for CHIP in practically all states, the family will face a more generous transfer by reducing their income to 133% of the FPL. In this case, the child will qualify for Medicaid in every state and the family will incur no premium payments and the lowest co-pay. If the family is willing to reduce their income further to 130% of the FPL, they will also gain eligibility for the Supplemental Nutrition Assistance Program (formerly Food Stamps).

Formal statistical tests are carried out to examine whether the average empirical rebound magnitude is consistent with the model predictions. Let $\bar{\delta}_S$ denote the average δ_s's for s between 1 and S: $\frac{1}{S}\sum_{s=1}^{S}\delta_s$, where the δ_s's are the coefficients in (11), and let $\delta^{e=0}$ be the rebound magnitude predicted by the model with $e = 0$. The baseline test is whether the average empirical rebound magnitude for the eleven months after starting a public insurance spell is as large as predicted: (1) H_0: $\bar{\delta}_{11} = \delta^{e=0}$ vs. H_1: $\bar{\delta}_{11} < \delta^{e=0}$. In light of the ambiguity introduced by receiving the renewal package 60 to 90 days prior to the end of the 12-month period, the potential strategic behavior for recertification may occur as early as during month 10. Therefore, I drop month 10 and 11 from the baseline in an alternative test: (2) H_0: $\bar{\delta}_9 = \delta^{e=0}$ vs. H_1: $\bar{\delta}_9 < \delta^{e=0}$. Finally, other tests are called for in the presence of seam bias. As noted in Pischke (1995) and Ham et al. (2009), seam bias

[16] $e = 0.15$ is the average Hicksian elasticities in the empirical micro literature for non-top income population as surveyed by Chetty (Forthcoming).

[17] Note that even $e = 0$, which corresponds to the case where the indifference curve in the flow utility is Leontief, still implies strategic behavior. This is the result of having a notch–as opposed to a kink–in the budget constraint.

is typically interpreted as the result of the "telescoping behavior"–survey respondents answer retrospective questions using their most recent status. In the most extreme scenario where every respondent telescopes in reporting public insurance coverage, which will imply the largest measurement error in the transitions into public insurance, the true month-0 income is observed only for those who actually start a public insurance spell in month 1. Assuming that there is equal probability of starting a spell in month 1, 2, 3 and 4 of a particular wave, then the expected dip-and-rebound magnitude is only a quarter of what is predicted by the neo-classical model. Hence, the final hypothesis I test is (3) H_0: $\bar{\delta}_8 = \frac{1}{4}\delta^{e=0}$ vs. H_1: $\bar{\delta}_8 < \frac{1}{4}\delta^{e=0}$ where I only include eight months of data because month 9 may be contaminated by the telescoping behavior in wave 3 after the start of the public insurance spell.

Table 6 presents the p-values associated with the three statistical tests above. The null hypothesis for all three tests are rejected based on all four samples (full and long gap sample for the 2001 and 2004 panels respectively) in favor of the alternative at the 5% level, except for test (3) in the 2001 panel full sample, which is rejected at the 10% level. To summarize, the empirical evidence points to little labor supply response and is in general inconsistent with the labor supply model. The findings likely imply frictions in income adjustments or that the perceived value of CHIP for families above the eligibility cutoff is lower than the expected government subsidy. Identifying the precise reason for the lack of strategic behavior is beyond the scope of this paper. With the labor supply responses practically ruled out, however, I will use a *mechanical* model in the subsequent analysis in the sense that incomes are drawn from a stochastic process as opposed to being controlled by the families. I compute the optimal continuous eligibility period length based on observed income processes from SIPP under various recertification cost parameters.

7 Optimal Length of the Continuous Eligibility Period

Because of the lack of income/labor supply responses to the continuous eligibility provision shown in section (6), I compute the optimal length of the recertification period for Medicaid/CHIP, τ, based on a mechanical model for individual behavior. In this model, labor supply considerations are absent from families' optimizing decisions and incomes simply follow a stochastic process. After the realization of income Z, consumption is determined by

$$C = [(1-t)Z + g]P + (1-t)Z(1-P)$$

where P is an indicator variable denoting program participation status, and agents' utility u only depends on the consumption level C.

In order to determine the optimal transfer policy, I specify next the social welfare function, which contains two components. The first component is a standard Bergson-Samuelson functional of weighted individual utilities, W, and the second component is surplus in the government's budget, S, which can be used to finance a public good (Salanie (2003)). I assume that the two components are additive and that the welfare resulting from the public good is linear in its spending. As an illustration, when eligibility check is performed every month and take-up rate is 100% (i.e. $P = 1_{[Z \leqslant \gamma]}$) and when eligibility monitoring is free, the per-period social welfare for each value of γ and t is given by:

$$\underbrace{\int \Psi(u(C(z)))f_Z(z)dz}_{W} + \omega \underbrace{[R - \Pr(Z \leqslant \gamma)g]}_{S} \tag{12}$$
$$\text{s.t.} \quad C(z) = [(1-t)z+g]1_{[z \leqslant \gamma]} + (1-t)z1_{[z>\gamma]}$$

Ψ is an increasing and concave function that weights the utilities of individual agents according to the social planner's redistributive taste, and ω reflects the contribution of S to overall social welfare relative to that of agents' utilities. t is the pre-determined marginal tax rates on income, and f_Z and F_Z specify the p.d.f and c.d.f. of pre-tax income Z respectively (assuming the stationarity of the income process which will be relaxed later). The government collects per-agent revenue R, which may contain income tax revenue $\int tzf_Z(z)dz$ as well as sources not explicitly modeled here,[18] and it is assumed that R is sufficiently large to cover program spending: $R \gg \Pr(Z \leqslant \gamma)g$.

The formulation of the social welfare function (12) differs slightly from a textbook approach (e.g., Salanie (2003)) in the follow respects. First, government surplus does not usually enter the social welfare function directly but through a balanced budget constraint. As mentioned above, however, the direct welfare impact of the S term can be attributed to its interpretation as spending on a public good (p. 81 Salanie (2003)). Salanie (2003) notes that the dependence of utility on S is neglected in his model because the spending on the public good is held constant. The specification (12) simply extends that of Salanie (2003) by allowing the production of the public good to be variable, and the additional advantage of this specification will be clear in the remainder of this subsection.

[18]For example, part of the federal CHIP funding comes from tobacco taxes.

Second, having a "notched" lump sum transfer schedule with the associated cutoff γ as the policy instrument is not prevalent in the optimal design literature. In fact, if the income tax schedule is completely flexible and that $\Psi \circ u$ is strictly concave, then the government should choose a transfer function that equalizes consumption across agents when labor supply decisions are not considered in the model (a special case is studied as early as in Edgeworth (1897)). When labor supply incentives are considered, the seminal paper of Mirrlees (1971) shows that the marginal tax rate always lies between zero and one which precludes a discrete drop in consumption as pre-tax income increases if the optimal tax schedule is completely flexible. However, Blinder and Rosen (1985) and Slemrod (2010) argue that it is possible to institute a notch as part of an optimal schedule when the set of income tax instruments is limited, e.g., linear.[19] Given their theoretical argument and the practical relevance of a notch-based transfer schedule, I continue with the specification of (12).

A dynamic extension of the baseline formulation (12) is called for when evaluating the optimal recertification period. I consider a T-period problem, where the public insurance program becomes available in period 1, and in every period, families' eligibility depends on their income and program participation history through the continuous eligibility provision. For example, when the continuous eligibility period is 3, a family is assumed to automatically participate in the program in period 2 and 3 if it was eligible and participated in the program in period 1. In period 4 when the family's eligibility is recertified, the participation status will depend on whether their period-4 income falls below the threshold. Formally, the social welfare function becomes

$$\begin{aligned} & \sum_{m=1}^{T} \beta^{m-1} E[\Psi(u(C_m - \phi R_m))] - \omega E[R - (gP_m + \kappa R_m)] \qquad (13) \\ \text{s.t.} \quad & C_m = [(1-t)Z_m + g]P_m + (1-t)Z_m(1-P_m) \end{aligned}$$

The expectation is taken over the joint distribution of $\{Z_1, ...Z_T\}$; P_m and R_m are dummy variables indicating whether a family participates in the program and whether program eligibility is certified in month m, and they are determined by the family income histories and the recertification period as illustrated above. In addition to spending on public insurance benefits, each eligibility check costs the government and the participating

[19] The *theoretical* properties of means-tested in-kind transfers in an optimal-design context have also been studied in Nichols and Zeckhauser (1982), Blackorby and Donaldson (1988), Gahvari (1995), Cremer and Gahvari (1997), Singh and Thomas (2000), etc., These studies typically consider the problem with two types of agents and a transfer scheme that ensures second-best allocation, i.e. the high type does not pretend to be the low type and claims benefit transfer. See Currie and Gahvari (2008) for a survey.

family κ and ϕ to perform, respectively.

In this paper, I consider the problem where the government chooses the continuous eligibility period τ to maximize social welfare taking tax rate t and eligibility cutoff γ as given (subsequently denoted by t^* and γ^*). Although it is tempting to cast the model in continuous time instead of (13) and analytically solve for τ, this approach is not feasible for the problem at hand due to its discrete nature. The dynamic budget constraints resulting from the continuous eligibility provision can only be specified discretely for each month, and it is not obvious how to formulate its continuous counterpart or even if it is at all possible. Therefore, I proceed to determine the optimal continuous eligibility period length by comparing numerically calculated social welfare corresponding to different recertification periods.

Obtaining the empirical income processes is crucial to the computation of social welfare. For the numerical exercise, I again rely on the 2001 and 2004 panels of SIPP but only keep the families that appear in all months of the panels for the observability of income processes over a long period of time (three years for the 2001 panel and four years for the 2004 panel, which translate to $T = 36$ and $T = 48$ for the two panels respectively). In my simulations, once I specify an eligibility recertification period, I can impute each family's monthly program participation decision based on its income history (assuming full take-up) and calculate its consumption accordingly.

The remaining missing piece for the numerical exercise of determining the optimal τ is specifying the value of ω and the functional form of Ψ. In order to obtain ω, I assume that the observed policy parameter γ^* is the solution to the frictionless optimization problem (12) where the cost of eligibility certification is zero. That is, the government abstracts away from the monitoring problem when determining the eligibility cutoff.[20] I can then solve for ω following the first order condition of γ as

$$\omega = \{\Psi([(1-t^*)\gamma^* + g]) - \Psi([(1-t^*)\gamma^*])\}/g \tag{14}$$

where individual utility u is assumed to be linear in consumption. For the weighting function Ψ, I follow Brewer et al. (2010) and specify $\Psi(u) = \frac{u^{1-\nu}}{1-\nu}$ with the redistributive taste parameter $\nu = 1$, and it follows that $\omega = \frac{1}{g}\log\frac{(1-t^*)\gamma^*+g}{(1-t^*)\gamma^*}$. Because each family faces different eligibility cutoffs, benefit notches and tax rates depending on its composition and income, I calculate ω using the average g, γ^* and t^* families face in SIPP similar to section (6), and the resulting value of ω is approximately 0.00026 in the both the 2001 and 2004

[20] ω will be smaller if monitoring cost is taken into consideration: $\omega = \{\Psi([(1-t^*)\gamma^* + g - \phi]) - \Psi([(1-t^*)\gamma^*])\}/(g+\kappa)$, and the resulting continuous eligibility period will be longer.

panels. Finally, β, the monthly discount rate is taken to be $(0.95)^{(1/12)}$.

In my simulations, I assume that families have no participation history prior to the beginning of the panel as mentioned above. This assumption precludes the possibility that a family with income above the eligibility cutoff can participate in the program at the very beginning of the panel. Consequently, families will incur a cost for eligibility check, ϕ, when they first become eligible during the panel (i.e. when I first observe their income dip below the cutoff). After identifying the first time a family participates in the program, participation status in the ensuing months can be determined under each specified continuous eligibility period length, τ, and the observed income process–in each month, families claim program benefits if they are still within the eligibility period or if their income is below the cutoff. With the ingredients g, t^*, γ^* and ω known for each family, I will be able to compute the welfare in (13) under combinations of τ, κ and ϕ.

Specifically, I choose $\tau = 1, 2, ..., 36$ months, and κ and ϕ take on the values of $0, $9.5, $19, $28.5 and $38 in 2010 dollars respectively. Note that 36 is the number of months in the SIPP 2001 panel, and so the data will not be informative for $\tau > 36$. The basis for the choices of κ is that the median hourly wage rate for government program interviewers is around $19 in May 2010 according to the Occupational Employment Statistics database of the Bureau of Labor Statistics, and the cost parameters correspond to 0, 0.5, 1, 1.5 and 2 hours of work for eligibility recertification respectively (similar estimates of recertification costs are carried out in Irvin et al. (2001)[21]). There is no formal reason to choose the same cost parameters for program participants as those for κ, and I do so here simply for convenience. In general, it may be more costly for a family to have their eligibility certified because it involves finding out information, gathering proof of incomes, filling out the application forms and sometimes traveling to meet face-to-face with their case worker on a work day. While $38 (2 hours of work for a case worker) is probably too high a cost on the government, it may not be unreasonable for a family trying to continue benefits.

Table 7 presents the optimal length of the continuous eligibility period from my simulations under the 25 combinations of κ and ϕ (5 values for κ and 5 for ϕ).[22] Not surprisingly, the government should certify eligibility every period when it is costless to do so and should check less frequently as costs increase. An

[21] Irvin et al. (2001) simulates the impact of implementing the 12-month continuous eligibility provision on Medicaid coverage, payment and administrative costs using program data for four states between 1994 and 1995. The study serves as a good benchmark, but it does not consider the potential labor supply effects of the implementation. Moreover, it does not model the impact under alternative lengths of the continuous eligibility period.

[22] Note that the prevalence of the optimal continuous eligibility periods that are multiples of 4 in Table 7 is a result of the 4-month seam structure of SIPP. Since most of the changes occur between waves, a τ which is not a multiple of 4 may lead to much more income change during the continuous eligibility period and is therefore less likely to be the maximizer of the social welfare function.

increase in the cost on families, ϕ, is more likely to lengthen the recertification period than an equal-sized increase in κ. The two SIPP panels give similar results on the optimal level τ. In particular, the estimates from both panels point to an optimal τ of 12 months for all values of κ when $\phi = \$19$, which may be reasonable and possibly an underestimate for the value of ϕ.

There are two caveats in interpreting the results of Table 7. First, given that the simulation sample consists of families that responded to interviews for all months during the SIPP panels, their income process may be different from those that are not included in the sample. Therefore, the resulting optimal length of the continuous eligibility period is sample-specific and may not apply for the general population. Second, I have so far abstracted away from the consideration of imperfect take-up and self-selection. Incorporating imperfect take-up may lengthen the optimal continuous eligibility period. In fact, simulations that allow random non-participation among eligible families point to longer optimal recertification periods, reflecting the cost in social welfare of having eligible families dropping out of insurance coverage due to frequent eligibility checks. When setting the monthly enrollment probability to be 12.5%, which amounts to an 80% annual participation rate as per Kaiser (2002-2011) assuming independent enrollment decision from month to month, the implied average optimal recertification period is 30 months or more under all cost parameter combinations. A related point is self-selection; that is, those who take up benefits place a particularly high valuation on program benefits, in which case there is variation in g across agents and possibly over time as well. Nichols and Zeckhauser (1982) argue that the government may consider imposing an "ordeal" mechanism so that only those most in need will select into the program, and one such "ordeal" is frequent eligibility checks. However, Currie and Grogger (2001) show that single-parent families, who were arguably among the most needy, disproportionately dropped out of the Food Stamp program when the frequency of recertifications had increased. This empirical example demonstrates that an ordeal mechanism may have the opposite effect than intended by Nichols and Zeckhauser (1982) if valuations of benefit and the severity of "ordeal" due to frequent recertifications are positively correlated for a given family. This correlation is key in a formal analysis of the effect of recertification frequency, and will be investigated in a future version of the paper.

8 Conclusion

This paper presents both a positive and normative analysis regarding the continuous eligibility provisions in a means-tested program. For the positive analysis, it investigates both theoretically and empirically the impact of continuous eligibility on the income and labor supply responses of program participants. Neo-classical labor supply models predict that a long eligibility recertification period provides strong dynamic opt-in incentives wherein families lower their income to gain program eligibility, acquire government-provided benefits for the continuous eligibility period and revert back to their "optimal" interior consumption bundle. Using the 2001 and 2004 panels from SIPP, I follow a flexible specification as in Jacobson et al. (1993) to describe the income and labor supply processes for families participating in Medicaid/CHIP and the point estimates do not indicate the dip-and-rebound strategic behavior around the time a child initially gains public insurance coverage. In addition, neo-classical dynamic labor supply models based on Saez (2010) are calibrated using family income and composition information, Medicaid/CHIP policy parameters and income tax rates. Comparing the magnitudes of the predicted strategic behavior to those observed empirically rejects the simple labor supply model in most subsamples.

With the positive analysis practically ruling out labor supply responses, I propose a framework utilizing the *mechanical* properties of the income processes in SIPP to answer the normative question: what the length of the continuous eligibility period should be. I derive a mapping from various combinations of cost parameters associated with eligibility recertification to the optimal length of the continuous eligibility period. Under moderate cost parameter values ($19 to the program participants for going through the application procedure), the evidence is suggestive that the optimal recertification period is no shorter than 12 months. Consequently, it may be beneficial for states currently allowing a 6-month renewal period to extend it to 12 months and for those currently adopting a 12-month renewal period to remain unchanged.

References

Altonji, Joseph G. and Christina H. Paxson, "Labor Supply, Hours Constraints, and Job Mobility," *The Journal of Human Resources*, 1992, *27* (2), pp. 256–278.

Ashenfelter, Orley, "Estimating the Effect of Training Programs on Earnings," *The Review of Economics and Statistics*, 1978, *60* (1), pp. 47–57.

_ , "Unemployment as Disequilibrium in a Model of Aggregate Labor Supply," *Econometrica*, 1980, *48* (3), pp. 547–564.

_ **and David Card**, "Using the Longitudinal Structure of Earnings to Estimate the Effect of Training Programs," *The Review of Economics and Statistics*, 1985, *67* (4), pp. 648–660.

Blackorby, Charles and David Donaldson, "Cash versus Kind, Self-Selection, and Efficient Transfers," *The American Economic Review*, 1988, *78* (4), pp. 691–700.

Blank, Rebecca M., "The Effect of Medical Need and Medicaid on AFDC Participation," *The Journal of Human Resources*, 1989, *24* (1), pp. 54–87.

Blinder, Alan S. and Harvey S. Rosen, "Notches," *The American Economic Review*, 1985, *75* (4), pp. 736–747.

Brewer, Mike, Emmanuel Saez, and Andrew Shephard, "Means-testing and tax rate on earnings," in J. Mirrlees, S. Adam, T. Besley, R. Blundell, S. Bond, R. Chot, M. Gammie, P. Johnson, G. Myles, and J. Poterba, eds., *Dimensions of Tax Design: The Mirrlees Review*, Oxford: Oxford University Press for the Institute for Fiscal Studies, 2010, chapter 2.

Browning, Martin, Angus Deaton, and Margaret Irish, "A Profitable Approach to Labor Supply and Commodity Demands over the Life-Cycle," *Econometrica*, 1985, *53* (3), pp. 503–544.

Card, David, Andrew K. G. Hildreth, and Lara D. Shore-Sheppard, "The Measurement of Medicaid Coverage in the SIPP: Evidence from a Comparison of Matched Records," *Journal of Business & Economic Statistics*, 2004, *22* (4), 410–420.

Chetty, Raj, "A New Method of Estimating Risk Aversion," *The American Economic Review*, 2006, *96* (5), 1821–1834.

_ , "Bounds on Elasticities with Optimization Frictions: A Synthesis of Micro and Macro Evidence on Labor Supply," *Econometrica*, Forthcoming.

_ **, John N. Friedman, Tore Olsen, and Luigi Pistaferri**, "Adjustment Costs, Firm Responses, and Micro vs. Macro Labor Supply Elasticities: Evidence from Danish Tax Records," *The Quarterly Journal of Economics*, 2011, *126* (2), 749–804.

CMS, "Title XXI Program Fact Sheets," Technical Report, Center for Medicare and Medicaid Services Various Years.

Cremer, Helmuth and Firouz Gahvari, "In-kind transfers, self-selection and optimal tax policy," *European Economic Review*, 1997, *41* (1), 97 – 114.

Currie, Janet, "The Take Up of Social Benefits," Working Paper 10488, National Bureau of Economic Research May 2004.

— **and Firouz Gahvari**, "Transfers in Cash and In-Kind: Theory Meets the Data," *Journal of Economic Literature*, 2008, *46* (2), pp. 333–383.

— **and Jeffrey Grogger**, "Explaining Recent Declines in Food Stamp Program Participation," *Brookings-Wharton Papers on Urban Affairs*, 2001, pp. pp. 203–244.

Dickens, William T. and Shelly J. Lundberg, "Hours Restrictions and Labor Supply," *International Economic Review*, 1993, *34* (1), pp. 169–192.

Edgeworth, F. Y., "The Pure Theory of Taxation," *The Economic Journal*, 1897, *7* (25), pp. 46–70.

Fairbrother, Gerry, Gowri Madhavan, Anthony Goudie, Joshua Watring, Rachel A. Sebastian, Lorin Ranbom, and Lisa A. Simpson, "Reporting on Continuity of Coverage for Children in Medicaid and CHIP: What States Can Learn from Monitoring Continuity and Duration of Coverage," *Academic Pediatrics*, 2011, *11* (4), 318 – 325.

Gahvari, Firouz, "In-kind Versus Cash Transfers In The Presence Of Distortionary Taxes," *Economic Inquiry*, 1995, *33* (1), 45–53.

Gruber, Jonathan, "Medicaid," in Robert A. Moffitt, ed., *Means-Tested Transfer Programs in the United States*, The University of Chicago Press, 2003, chapter 1.

— **and Kosali Simon**, "Crowd-out 10 years later: Have recent public insurance expansions crowded out private health insurance?," *Journal of Health Economics*, 2008, *27* (2), 201 – 217.

Ham, John C., "Estimation of a Labour Supply Model with Censoring Due to Unemployment and Underemployment," *The Review of Economic Studies*, 1982, *49* (3), pp. 335–354.

— **, Xianghong Li, and Lara Shore-Sheppard**, "Seam Bias, Multiple-State, Multiple-Spell Duration Models and the Employment Dynamics of Disadvantaged Women," Working Paper 15151, National Bureau of Economic Research July 2009.

Irvin, Carol, Deborah Peikes, Chris Trenholm, and Nazmul Khan, "Discontinuous Coverage in Medicaid and the Implications of 12-Month Continuous Coverage for Children: Final Report," Technical Report, Mathematica Policy Research 2001.

Jacobson, Louis S., Robert J. LaLonde, and Daniel G. Sullivan, "Earnings Losses of Displaced Workers," *The American Economic Review*, 1993, *83* (4), pp. 685–709.

Kabbani, Nader S. and Parke E. Wilde, "Short Recertification Periods in the U.S. Food Stamp Program," *The Journal of Human Resources*, 2003, *38*, pp. 1112–1138.

Kahn, Shulamit and Kevin Lang, "The Effect of Hours Constraints on Labor Supply Estimates," *The Review of Economics and Statistics*, 1991, *73* (4), pp. 605–611.

Kaiser, "A 50 State Update on Eligibility Rules, Enrollment and Renewal Procedures, and Cost-Sharing Practices in Medicaid and SCHIP," Technical Report, The Henry J. Kaiser Family Foundation 2002-2011.

Kleven, Henrik Jacobsen and Mazhar Waseem, "Tax Notches in Pakistan: Tax Evasion, Real Responses, and Income Shifting," Working Paper, London School of Economics 2011.

Kornfeld, Robert, "Explaining Recent Trends in Food Stamp Program Caseload," E-FAN-02-008, U.S. Department of Agriculture, Economic Research Service 2002.

MaCurdy, Thomas E., "An Empirical Model of Labor Supply in a Life-Cycle Setting," *Journal of Political Economy*, 1981, *89* (6), pp. 1059–1085.

Mirrlees, J. A., "An Exploration in the Theory of Optimum Income Taxation," *The Review of Economic Studies*, 1971, *38* (2), pp. 175–208.

Moffitt, Robert, "An Economic Model of Welfare Stigma," *The American Economic Review*, 1983, *73* (5), pp. 1023–1035.

NGA, "Maternal and Child Health Update," Technical Report, National Governors Association 2000-2008.

Nichols, Albert L. and Richard J. Zeckhauser, "Targeting Transfers through Restrictions on Recipients," *The American Economic Review*, 1982, *72* (2), pp. 372–377.

Olson, Lynn M., Suk fong S. Tang, and Paul W. Newacheck, "Children in the United States with Discontinuous Health Insurance Coverage," *New England Journal of Medicine*, 2005, *353* (4), 382–391.

Pischke, Jörn-Steffen, "Individual Income, Incomplete Information, and Aggregate Consumption," *Econometrica*, 1995, *63* (4), pp. 805–840.

Saez, Emmanuel, "Do Taxpayers Bunch at Kink Points?," Working Paper 7366, National Bureau of Economic Research, September 1999.

_ , "Do Taxpayers Bunch at Kink Points?," Working Paper, NBER-TAPES Conference, 2002.

_ , "Do Taxpayers Bunch at Kink Points?," *American Economic Journal: Economic Policy*, 2010, *2(3)*, 180 – 212.

Salanie, Bernard, *The Economics of Taxation*, The MIT Press, 2003.

Singh, Nirvikar and Ravi Thomas, "Welfare Policy: Cash versus Kind, Self-Selection and Notches," *Southern Economic Journal*, 2000, *66* (4), pp. 976–990.

Slemrod, Joel, "Buenas Notches: Lines and Notches in Tax System Design," Working Paper September 2010. First Draft: March 2010.

Yelowitz, Aaron S., "The Medicaid Notch, Labor Supply, and Welfare Participation: Evidence from Eligibility Expansions," *The Quarterly Journal of Economics*, 1995, *110(4)*, 909–939.

Appendix

States Providing Continuous Eligibility and Presumptive Eligibility

Continuous Eligibility

- The states that provided 12 months of continuous coverage in the sample period (2001-2007) are: Alabama, California, Washington D.C., Idaho, Illinois, Iowa, Kansas, Louisiana, Mississippi, Maine, Michigan (after Jan 2003), New York, North Carolina, Ohio, Pennsylvania, South Carolina, Washington, and West Virginia (after Oct 2002).
- The states that did not provide 12 months of continuous eligibility are: Colorado, Georgia, Hawaii, Kentucky, Missouri, Montana, Nevada, New Hampshire, North Dakota, Oklahoma, Rhode Island, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Wisconsin, and Wyoming.[23]
- In the states that remain–Alaska, Arizona, Arkansas, Connecticut, Delaware, Florida, Indiana, Maryland, Massachusetts, Minnesota, Nebraska, New Jersey, New Mexico, and Oregon–the rules for continuous eligibility are complicated with changes or different implementations for different programs during my sample period, and are thus dropped from my analysis sample.

Presumptive Eligibility

- The states that provided presumptive eligibility are California, Connecticut, Florida, Illinois, Massachusetts, Michigan, Missouri, Nebraska, New Hampshire, New Jersey, New York and Oklahoma.

Discrete Labor Supply Choices

In this section, I show that there is no income bunching but a discontinuity in the income density at the eligibility cutoff in the case where finitely many choices of hours are allowed. Formally, let the menu of labor supply choices be $\{h_1, h_2, ..., h_d\}$ where $0 = h_1 < h_2 < ... < h_d = 1$. For each w, let $\bar{n}_{h_i,h_{i+1}}(w)$, $i = 1,2,...d$, be the type of agent indifferent between choosing $H = h_i$ and $H = h_{i+1}$, and it follows that agents facing wage w of type $n \in (\bar{n}_{h_{i-1},h_i}(w), \bar{n}_{h_i,h_{i+1}}(w)]$ choose $H = h_i$.[24] $\bar{n}_{h_i,h_{i+1}}(w)$ varies smoothly with w except when $wh_i = \gamma$ and $wh_{i+1} = \gamma$. There is a discontinuous increase when $w = \gamma/h_{i+1}$ and a discontinuous decrease

[23] Note that many of the states that did not provide continuous eligibility allowed a 12-month renewal period.

[24] $\bar{n}_{h_d,h_{d+1}}$ is defined to be ∞.

when $w = \gamma/h_i$. The c.d.f. of Z at $z > 0$ is

$$F_Z(Z < z) = \Pr(H = 0) + \sum_{i=2}^{d} \int_0^{z/h_i} \int_{\bar{n}_{h_{i-1},h_i}(w')}^{\bar{n}_{h_i,h_{i+1}}(w')} f_{n,w}(n', w') dn' dw'$$

F_Z is continuous at γ because $\bar{n}_{h_i,h_{i+1}}(w)$ is right continuous for all i and that $f_{n,w}$ is continuous. However,

$$\begin{aligned} \lim_{z\uparrow\gamma} f_Z(z) &= \textstyle\sum_{i=2}^{d} \frac{1}{h_i} \int_{\bar{n}^l_{h_{i-1},h_i}(\gamma/h_i)}^{\bar{n}^l_{h_i,h_{i+1}}(\gamma/h_i)} f_{n,w}(n', \frac{\gamma}{h_i}) dn' \\ \lim_{z\downarrow\gamma} f_Z(z) &= \textstyle\sum_{i=2}^{d} \frac{1}{h_i} \int_{\bar{n}^r_{h_{i-1},h_i}(\gamma/h_i)}^{\bar{n}^r_{h_i,h_{i+1}}(\gamma/h_i)} f_{n,w}(n', \frac{\gamma}{h_i}) dn' \end{aligned}$$

where

$$\begin{aligned} \bar{n}^l_{h_i,h_{i+1}}(\frac{\gamma}{h_i}) &\equiv \lim_{w\uparrow(\frac{\gamma}{h_i})} \bar{n}_{h_i,h_{i+1}}(w) > \lim_{w\downarrow(\frac{\gamma}{h_i})} \bar{n}_{h_i,h_{i+1}}(w) \equiv \bar{n}^r_{h_i,h_{i+1}}(\frac{\gamma}{h_i}) \\ \bar{n}^l_{h_{i-1},h_i}(\frac{\gamma}{h_i}) &\equiv \lim_{w\uparrow(\frac{\gamma}{h_i})} \bar{n}_{h_{i-1},h_i}(w) < \lim_{w\downarrow(\frac{\gamma}{h_i})} \bar{n}_{h_{i-1},h_i}(w) \equiv \bar{n}^r_{h_{i-1},h_i}(\frac{\gamma}{h_i}) \end{aligned}$$

It follows that

$$\int_{\bar{n}^r_{h_{i-1},h_i}(\gamma/h_i)}^{\bar{n}^r_{h_i,h_{i+1}}(\gamma/h_i)} f_{n,w}(n', \frac{\gamma}{h_i}) dn' < \frac{1}{h_i} \int_{\bar{n}^l_{h_{i-1},h_i}(\gamma/h_i)}^{\bar{n}^l_{h_i,h_{i+1}}(\gamma/h_i)} f_{n,w}(n', \frac{\gamma}{h_i}) dn'$$

for all i, and therefore $\lim_{z\uparrow\gamma} f_Z(z) > \lim_{z\downarrow\gamma} f_Z(z)$.

Table 1: Total Counts of Individuals and Sample Units and Those Covered by Public Insurance During Panel

(a) Total Individual and Sample Unit Counts

	No. of Individuals		No. of SU's	
	2001	2004	2001	2004
Total	104053	131549	35106	43540
Children Living with Parent(s)	29549	37333	14323	17780

(b) Individual and Sample Unit Counts: on Public Insurance During Panel

	No. of Individuals on Public Insurance		No. of SU's on Public Insurance	
	2001	2004	2001	2004
Total	23152	33986	10001	14454
Children Living with Parent(s)	11109	17458	5272	8235

Notes: Panel (a) shows the total number of children, individuals and sample units in the 2001 and 2004 SIPP panels. The bottom row of the right column shows number of sample units that have children living with parents. Panel (b) shows the total number of children, individuals and sample units ever on public insurance. The top row of the right column shows the number of sample units that had at least a member on public insurance during the panel, and the bottom row shows the number of sample units that had at least a child on public insurance during the panel.

Table 2: Public Insurance Spell, Child and Sample Unit Counts by Spell Types, Continuous Eligibility States and Analysis Sample

(a) Public Insurance Spell, Child and Sample Unit Counts by Spell Types and Continuous Eligibility States

	Total No. of Public Insurance Spells		No. of Kids with Public Insurance Spells		No. of SU with Kids on Public Insurance	
	2001	2004	2001	2004	2001	2004
Pub Insurance spells	16109	23109	10656	17190	5024	8149
Left-Truncated Spells	8402	13996	7407	11929	3683	5848
Fresh Spells	7707	9113	5759	7850	3033	4390
Fresh Spells Ex. Infants & State Movers & SSI Kids	7158	8321	5360	7188	2866	4099
12-Month Continuous Elig.	3096	3312	2310	2843	1257	1642
No Continuous Elig.	2270	2535	1742	2217	934	1255
Other States	1792	2474	1319	2147	685	1223

(b) Public Insurance Spell, Child and Sample Unit Counts in Analysis Sample

	Subsample Public Insurance Spells		No. of Kids with Public Insurance Spells		No. of SU with Kids on Public Insurance	
	2001	2004	2001	2004	2001	2004
Fresh Spells: States with 12 Months of Continuous Elig.	3096	3312	2310	2843	1257	1642
Long Gap Sample	501	815	501	804	302	494
Long Gap and No Presumptive Elig.	232	389	232	382	134	232

Notes: This table shows the number of observations excluded in each subsample. The full analysis sample consists of 3096 spells from 2310 children in 1257 sample units in the 2001 panel and 3312 spells from 2843 children in 1642 sample units in the 2004 panel. For the 2001 panel, the analysis sample is reached by excluding 8402 left-truncated Spells, 549 spells from infants and children in families that moved during the panel, and 4062 spells from children not in the states that provide continuous eligibility. For the 2004 panel, the analysis sample is reached by excluding 13996 left-truncated Spells, 792 spells from infants and children in families that moved during the panel, and 5009 spells from children not in the states that provide continuous eligibility.

Table 3: Variable Means for Children in Analysis Samples

	2001 Panel				2004 Panel			
	Full Sample		Long Gap Sample		Full Sample		Long Gap Sample	
	Month 0	Month 1	Month 0	Month 1	Month 0	Month 1	Month 0	Month 1
Age	8.17	8.26	9.15	9.14	8.76	8.85	9.27	9.36
Female	0.5	0.5	0.5	0.5	0.48	0.48	0.5	0.5
Black	0.25	0.25	0.2	0.2	0.17	0.17	0.12	0.11
Family Size	4.1	4.1	4.12	4.13	4	4	4.2	4.2
Single Parent Family	0.49	0.49	0.38	0.38	0.41	0.41	0.27	0.27
Family Income (nominal)	2139	2048	2914	2847	3585	3615	4860	4828
Family Income (in 2010 $)	2582	2468	3481	3396	3990	4014	5312	5268
Fraction without Earnings	0.11	0.12	0.05	0.07	0.08	0.07	0.04	0.05
On Welfare	0.05	0.07	0.01	0.02	0.03	0.04	0.01	0.01
On Medicaid	0	1	0	1	0	1	0	1
On Private Insurance	0.35	0.26	0.42	0.31	0.5	0.46	0.63	0.57
Mom on Medicaid	0.19	0.36	0.07	0.24	0.18	0.27	0.01	0.15
Dad on Medicaid	0.08	0.16	0.03	0.1	0.07	0.12	0.04	0.07
Mom on Private Insurance	0.36	0.3	0.47	0.41	0.54	0.52	0.69	0.68
Dad on Private Insurance	0.43	0.38	0.52	0.47	0.66	0.65	0.77	0.77
Mom on UI	0.02	0.02	0.03	0.04	0.01	0.02	0.02	0.02
Dad on UI	0.05	0.05	0.07	0.08	0.03	0.02	0.02	0.03

Notes: Variable means for children and their families in the various analysis samples right before (Month 0) and during the first month (Month 1) of public insurance spell.

Table 4: Empirical vs. Predicted Income Dip and Rebound Measures for Various Labor Supply Elasticities: SIPP 2001 Panel

	Empirical Responses		Empirical Responses		Model Predicted Responses			Model Predicted Responses		
	Full Sample		Long Gap Sample		No Income Effects ($\rho = 0$)			With Income Effects ($\rho = 0.74$)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Month in Spell	Point Estimates	Upper 95% CI	Point Estimates	Upper 95% CI	e=0.15	e=0.05	e=0	e=0.15	e=0.05	e=0
-11	-124	217	49	763	661	494	415	480	428	415
-10	46	280	148	815	661	494	415	480	428	415
-9	-99	222	36	735	661	494	415	480	428	415
-8	-14	294	97	751	661	494	415	480	428	415
-7	69	318	170	838	661	494	415	480	428	415
-6	10	247	17	661	661	494	415	480	428	415
-5	64	302	33	677	661	494	415	501	435	415
-4	34	239	29	565	661	494	415	501	435	415
-3	-54	64	-229	305	661	494	415	501	435	415
-2	-57	31	-200	216	661	494	415	501	435	415
-1	-23	62	-132	285	661	494	415	501	435	415
0	0	0	0	0	0	0	0	0	0	0
1	-77	39	-230	214	661	494	415	480	428	415
2	-50	77	-191	294	661	494	415	480	428	415
3	-28	113	-143	351	661	494	415	480	428	415
4	-16	143	-259	269	661	494	415	480	428	415
5	-68	141	-512	183	661	494	415	480	428	415
6	-40	186	-515	221	661	494	415	480	428	415
7	-77	243	-557	220	661	494	415	501	435	415
8	-50	292	-624	184	661	494	415	501	435	415
9	-28	393	-731	192	661	494	415	501	435	415
10	-16	337	-736	202	661	494	415	501	435	415
11	-69	381	-582	398	661	494	415	501	435	415

Notes: Empirical estimates are based on specification (11) where the point estimates trace out average family income in 2010 dollars around the start of a child's public insurance spell. Model parameters are calibrated using 2001 SIPP panel income data, federal income tax rates, published Medicaid/CHIP eligibility cutoffs and CHIP spending data.

Table 5: Empirical vs. Predicted Income Dip and Rebound Measures for Various Labor Supply Elasticities: SIPP 2004 Panel

	Empirical Responses		Empirical Responses		Model Predicted Responses			Model Predicted Responses		
	Full Sample		Long Gap Sample		No Income Effect (ρ=0)			With Income Effect (ρ=0.74)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Month in Spell	Point Estimates	Upper 95% CI	Point Estimates	Upper 95% CI	e=0.15	e=0.05	e=0	e=0.15	e=0.05	e=0
-11	407	944	517	1355	687	524	388	508	412	388
-10	462	995	536	1391	687	524	388	508	412	388
-9	302	786	348	1158	687	524	388	508	412	388
-8	388	914	361	1172	687	524	388	508	412	388
-7	101	403	243	908	687	524	388	508	412	388
-6	119	423	267	932	687	524	388	508	412	388
-5	128	458	259	939	687	524	388	531	420	388
-4	75	382	147	852	687	524	388	531	420	388
-3	-28	130	27	415	687	524	388	531	420	388
-2	-27	122	51	427	687	524	388	531	420	388
-1	-77	41	1	160	687	524	388	531	420	388
0	0	0	0	0	0	0	0	0	0	0
1	23	242	-245	35	687	524	388	508	412	388
2	-3	261	-356	-40	687	524	388	508	412	388
3	-40	197	-510	-134	687	524	388	508	412	388
4	-43	201	-607	-196	687	524	388	508	412	388
5	-250	-23	-686	-140	687	524	388	508	412	388
6	-342	-112	-753	-182	687	524	388	508	412	388
7	-363	-127	-884	-284	687	524	388	531	420	388
8	-346	-96	-908	-262	687	524	388	531	420	388
9	-353	5	-1035	44	687	524	388	531	420	388
10	-374	44	-684	849	687	524	388	531	420	388
11	-452	-43	-1350	-166	687	524	388	531	420	388

Notes: Empirical estimates are based on specification (11) where the point estimates trace out average family income in 2010 dollars around the start of a child's public insurance spell. Model parameters are calibrated using 2004 SIPP panel income data, federal income tax rates, published Medicaid/CHIP eligibility cutoffs and CHIP spending data.

Table 6: Statistical Tests of Theoretical Predictions

	p-values from SIPP 2001 Panel		p-values from SIPP 2004 Panel	
	Full Sample	Long Gap Sample	Full Sample	Long Gap Sample
(1) H_0: $\bar{\bar{\delta}}_{11} = \delta^{e=0}$ vs. H_1: $\bar{\bar{\delta}}_{11} < \delta^{e=0}$	0.000***	0.003***	0.000***	0.000***
(2) H_0: $\bar{\bar{\delta}}_{9} = \delta^{e=0}$ vs. H_1: $\bar{\bar{\delta}}_{9} < \delta^{e=0}$	0.000***	0.003***	0.000***	0.000***
(3) H_0: $\bar{\bar{\delta}}_{8} = \frac{1}{4}\delta^{e=0}$ vs. H_1: $\bar{\bar{\delta}}_{8} < \frac{1}{4}\delta^{e=0}$	0.059*	0.047**	0.004***	0.000***

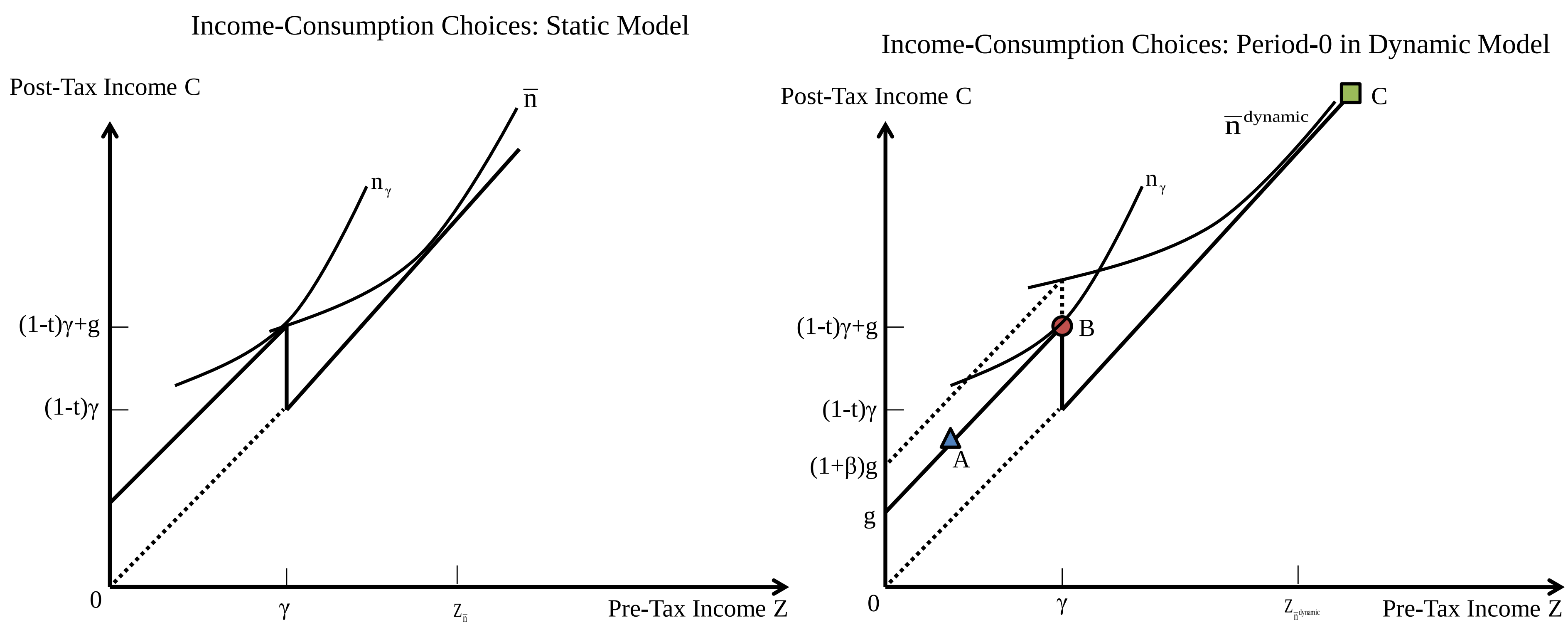
Notes: Presented are p-values from statistical tests of theoretical predictions based on the neo-classical model in subsection (3.2) with $e = 0$. Test (1) is the baseline, (2) incorporates the timing of the receipt of the renewal package and (3) incorporates seam bias as discussed in section (6).
* p<0.1; ** p<0.05; *** p<0.001.

Table 7: Optimal Length of the Continuous Eligibility Period from Simulations

Cost of Recertification		Optimal Length of the Continuous Eligibility Period (τ)	
ϕ (in 2010 dollars)	κ (in 2010 dollars)	SIPP 2001 Panel	SIPP 2004 Panel
$0	$0	1	1
$0	$9.5	4	4
$0	$19	4	4
$0	$28.5	4	4
$0	$38	6	8
$9.5	$0	6	4
$9.5	$9.5	8	8
$9.5	$19	9	8
$9.5	$28.5	12	8
$9.5	$38	12	12
$19	$0	12	12
$19	$9.5	12	12
$19	$19	12	12
$19	$28.5	12	12
$19	$38	12	12
$28.5	$0	12	12
$28.5	$9.5	12	12
$28.5	$19	18	12
$28.5	$28.5	18	16
$28.5	$38	18	16
$38	$0	18	16
$38	$9.5	18	16
$38	$19	18	16
$38	$28.5	18	24
$38	$38	18	24

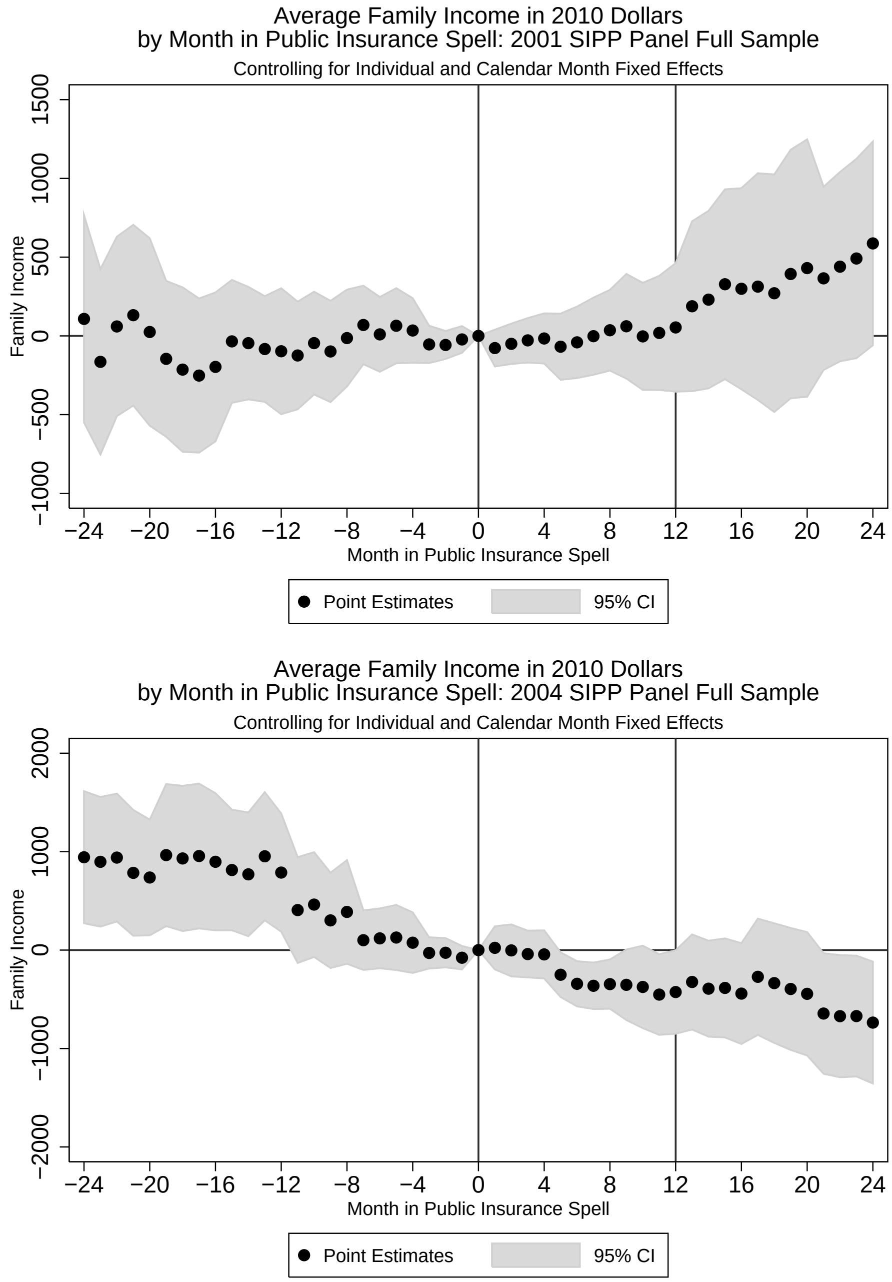
Notes: The optimal lengths of the continuous eligibility period, τ, are calculated based on the model in section (7). The choice set of τ is $\{1, 2, ..., 36\}$, and details regarding the model parameters and specification are presented in section (7). The simulation sample consists of families who responded to SIPP interviews for every month during the 2001 and 2004 panels.

Figure 1: Income-Consumption Choices in the Static and Dynamic Models



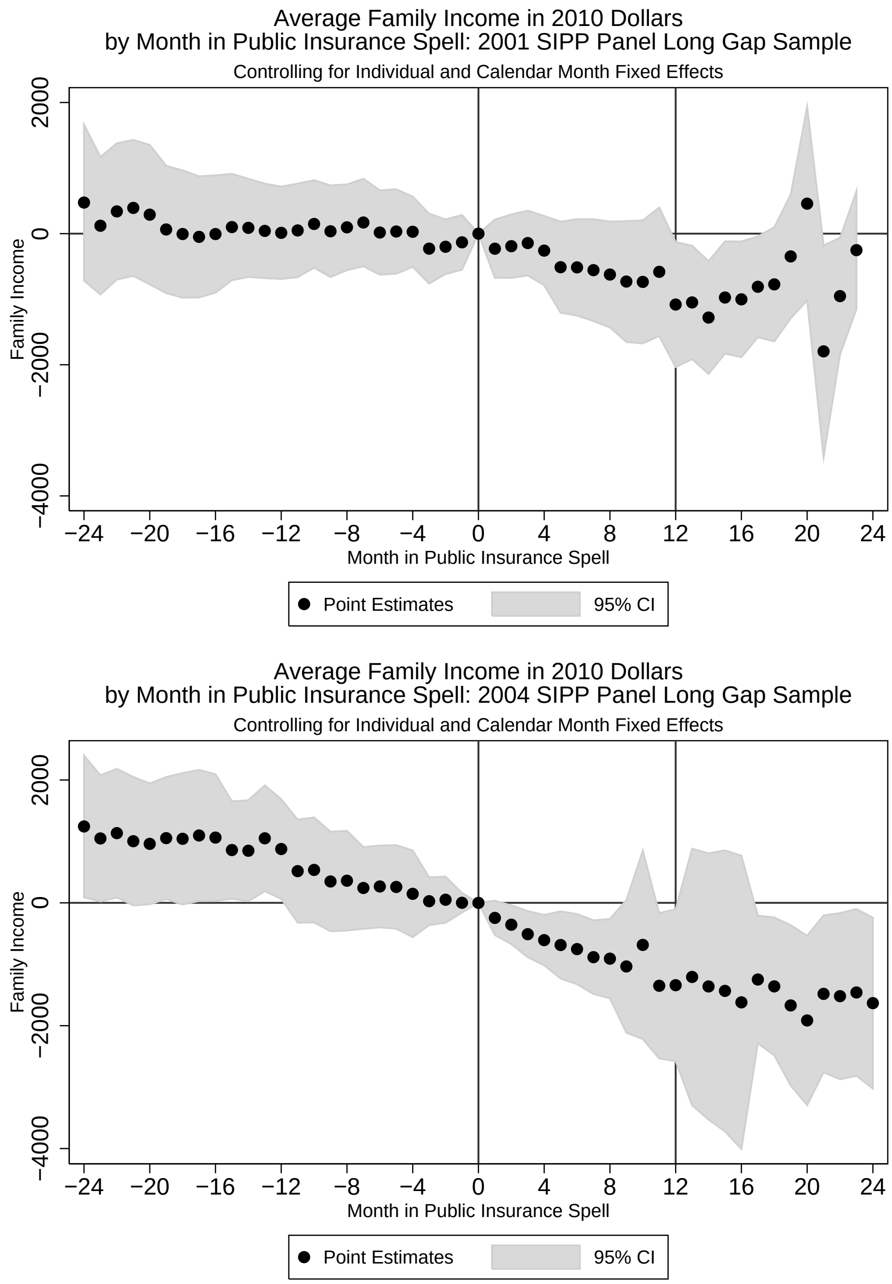
Notes: The left and right panels illustrate agents' income-consumption choices in the static (subsection 3.1.1) and dynamic model (subsection 3.2) respectively. The static model assumes that income eligibility is checked every period whereas it is checked every two periods in the dynamic model. In the case of the static model which is presented in the left panel, agents whose type is in the interval $[n_\gamma, \bar{n}]$ choose pre-tax income $Z = \gamma$. For the 2-period dynamic model which is presented in the right panel, agents whose type is in the interval $[n_\gamma, \bar{n}^{dynamic}]$ choose pre-tax income γ in period 0. The fact that eligibility is only checked once every two periods in effect increases the size of the benefit notch from g to $(1+\beta)g$.

Figure 2: Average Family Income by Month in Medicaid Spell: Full Sample



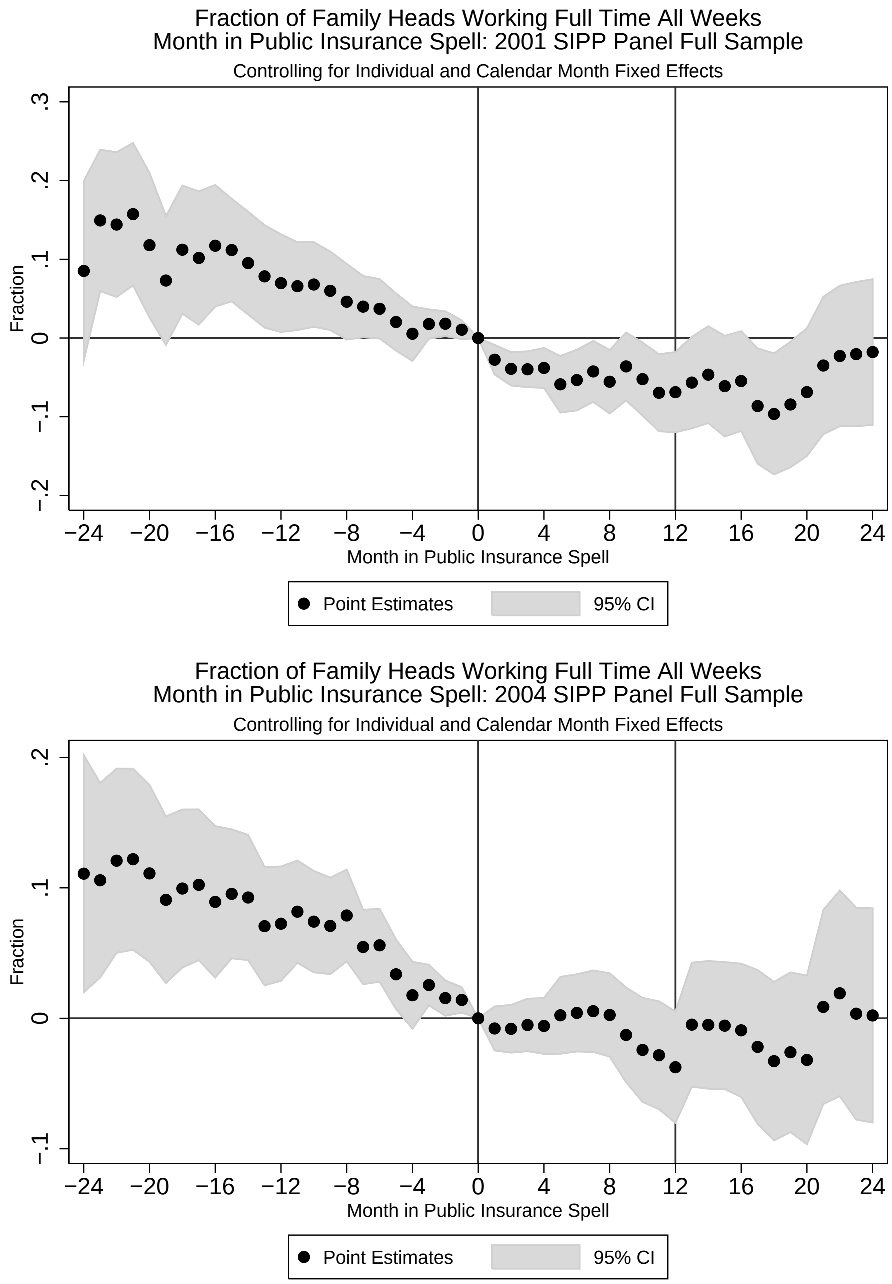
Notes: Plotted are coefficients from regressions of family monthly income in 2010 dollars on a set of indicator variables for months before or since the start of a fresh Medicaid/CHIP spell. The top panel plots the coefficients from the SIPP 2001 panel and the bottom plots those from the 2004 panel. The regression includes individual and calendar month fixed effects. The standard error is clustered at the SIPP sampling unit level. Month 0 (the month right before the start of a fresh Medicaid/CHIP spell) is the omitted category, and the corresponding coefficient is 0 by construction. The sample in the 2001 panel includes 3096 fresh spells for 2310 children from 1257 sample units, and the 2004 panel sample includes 3312 fresh spells for 2843 children from 1642 sample units. The sample is truncated by discarding the observations with Medicaid coverage before the start of a spell and those without Medicaid coverage after.

Figure 3: Average Family Income by Month in Medicaid Spell: Long Gap Sample



Notes: Plotted are coefficients from regressions of family monthly income in 2010 dollars on a set of indicator variables for months before or since the start of a fresh Medicaid/CHIP spell. The top panel plots the coefficients from the SIPP 2001 panel and the bottom plots those from the 2004 panel. The regression includes individual and calendar month fixed effects. The standard error is clustered at the SIPP sampling unit level. Month 0 (the month right before the start of a fresh Medicaid/CHIP spell) is the omitted category, and the corresponding coefficient is 0 by construction. The sample only includes children who were not covered by public insurance for 12 months before the start of a spell. The 2001 panel sample includes 501 fresh spells for 501 children from 302 sample units, and the 2004 panel sample includes 815 fresh spells for 804 children from 494 sample units. The sample is truncated by discarding the observations with Medicaid coverage before the start of a spell and those without Medicaid coverage after.

Figure 4: Fraction of Family Head Working Full Time in Medicaid Spell: Full Sample



Notes: Plotted are coefficients from regressions of the indicator of whether the family head worked full time on a set of indicator variables for months before or since the start of a fresh Medicaid/CHIP spell. The top panel plots the coefficients from the SIPP 2001 panel and the bottom plots those from the 2004 panel. The regression includes individual and calendar month fixed effects. The standard error is clustered at the SIPP sampling unit level. Month 0 (the month right before the start of a fresh Medicaid/CHIP spell) is the omitted category, and the corresponding coefficient is 0 by construction. The sample in the 2001 panel includes 3096 fresh spells for 2310 children from 1257 sample units, and the 2004 panel sample includes 3312 fresh spells for 2843 children from 1642 sample units. The sample is truncated by discarding the observations with Medicaid coverage before the start of a spell and those without Medicaid coverage after.

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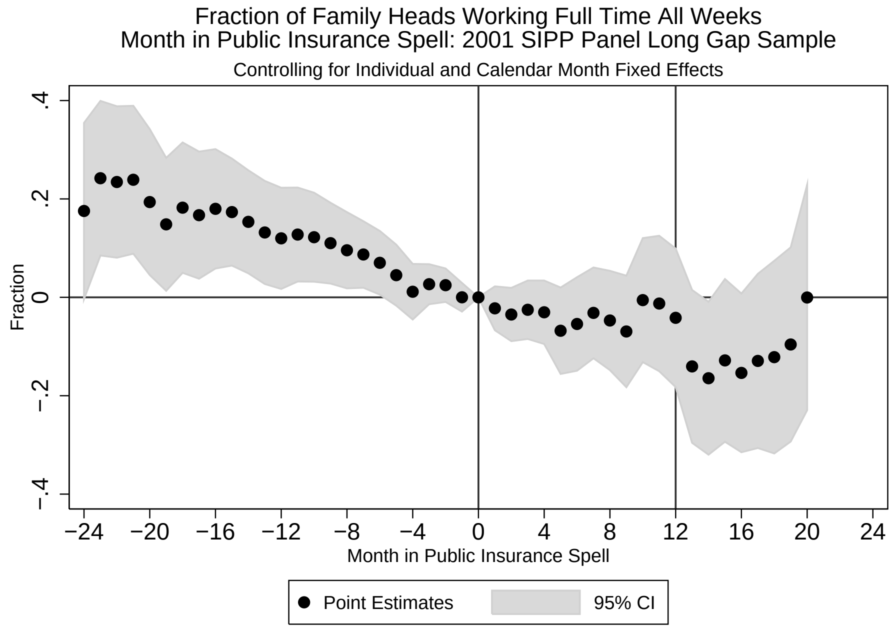
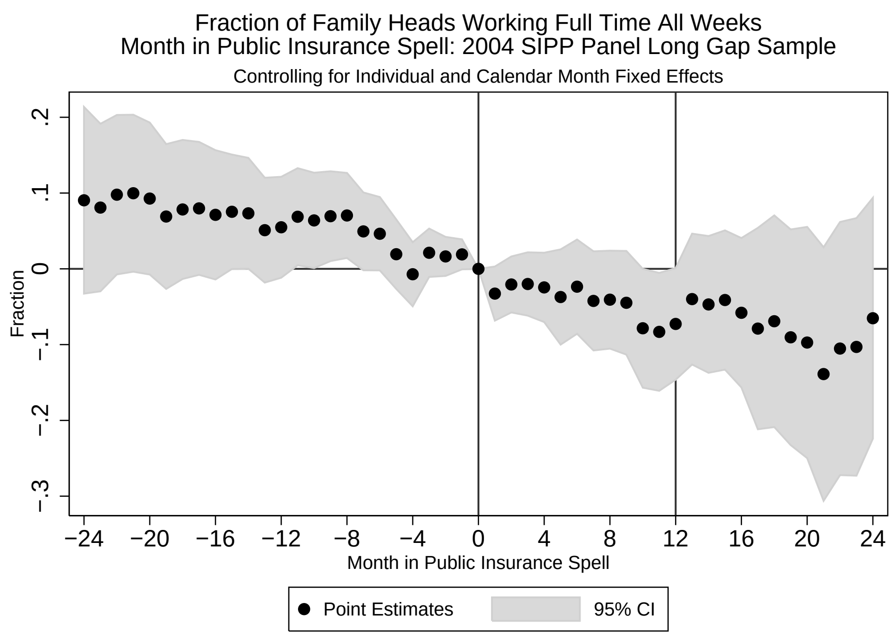
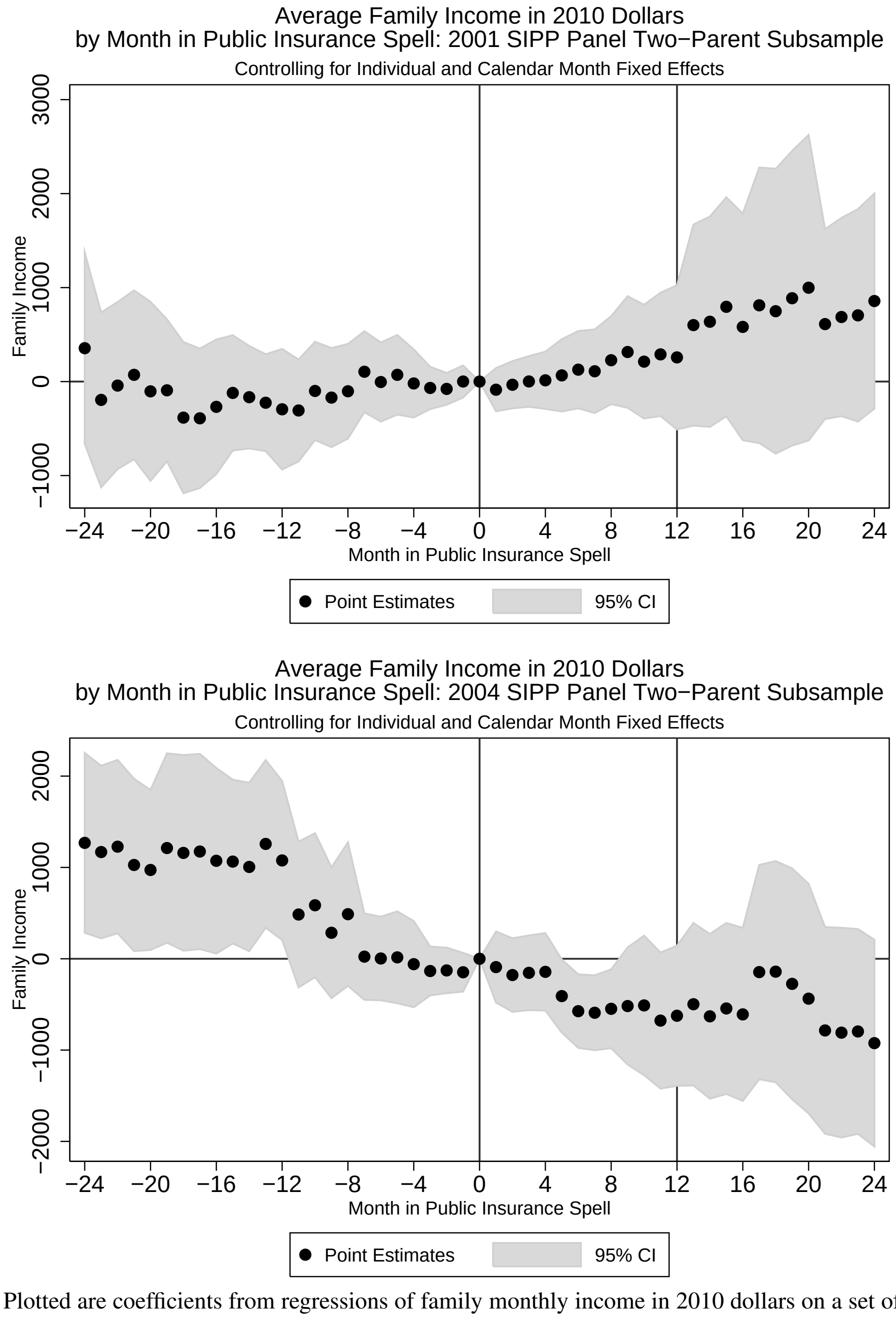




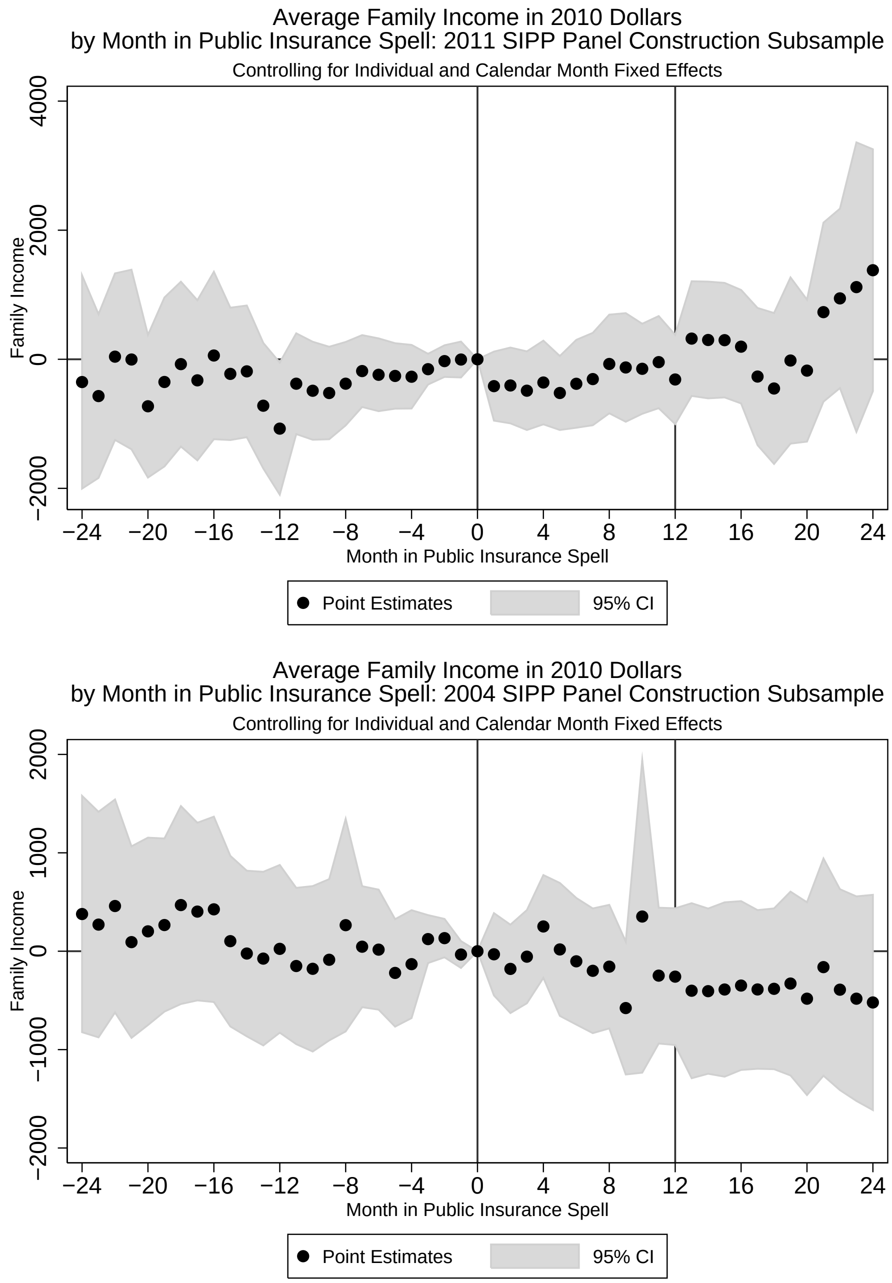
Notes: Plotted are coefficients from regressions of the indicator of whether the family head worked full time on a set of indicator variables for months before or since the start of a fresh Medicaid/CHIP spell. The top panel plots the coefficients from the SIPP 2001 panel and the bottom plots those from the 2004 panel. The regression includes individual and calendar month fixed effects. The standard error is clustered at the SIPP sampling unit level. Month 0 (the month right before the start of a fresh Medicaid/CHIP spell) is the omitted category, and the corresponding coefficient is 0 by construction. The sample only includes children who were not covered by public insurance for 12 months before the start of a spell. The 2001 panel sample includes 501 fresh spells for 501 children from 302 sample units, and the 2004 panel sample includes 815 fresh spells for 804 children from 494 sample units. The sample is truncated by discarding the observations with Medicaid coverage before the start of a spell and those without Medicaid coverage after.

Figure 6: Average Family Income by Month in Medicaid Spell: Subsample with Two-Parent Families



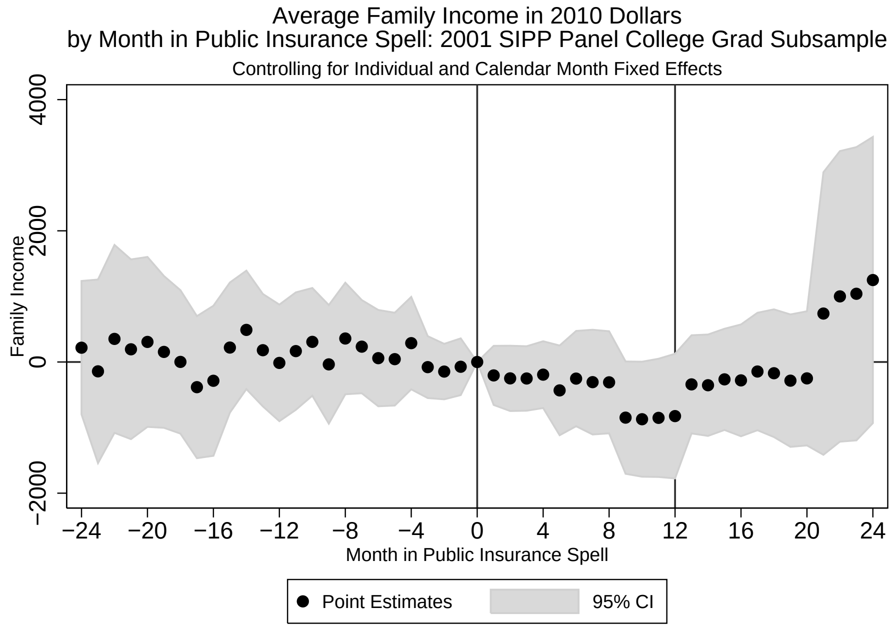
Notes: Plotted are coefficients from regressions of family monthly income in 2010 dollars on a set of indicator variables for months before or since the start of a fresh Medicaid/CHIP spell for children living with both parents in the sample period. The top panel plots the coefficients from the SIPP 2001 panel and the bottom plots those from the 2004 panel. The regression includes individual and calendar month fixed effects. The standard error is clustered at the SIPP sampling unit level. Month 0 (the month right before the start of a fresh Medicaid/CHIP spell) is the omitted category, and the corresponding coefficient is 0 by construction. The 2001 panel sample includes 1472 fresh spells for 1106 children from 578 sample units, and the 2004 panel sample includes 1860 fresh spells for 1630 children from 903 sample units. The sample is truncated by discarding the observations with Medicaid coverage before the start of a spell and those without Medicaid coverage after.

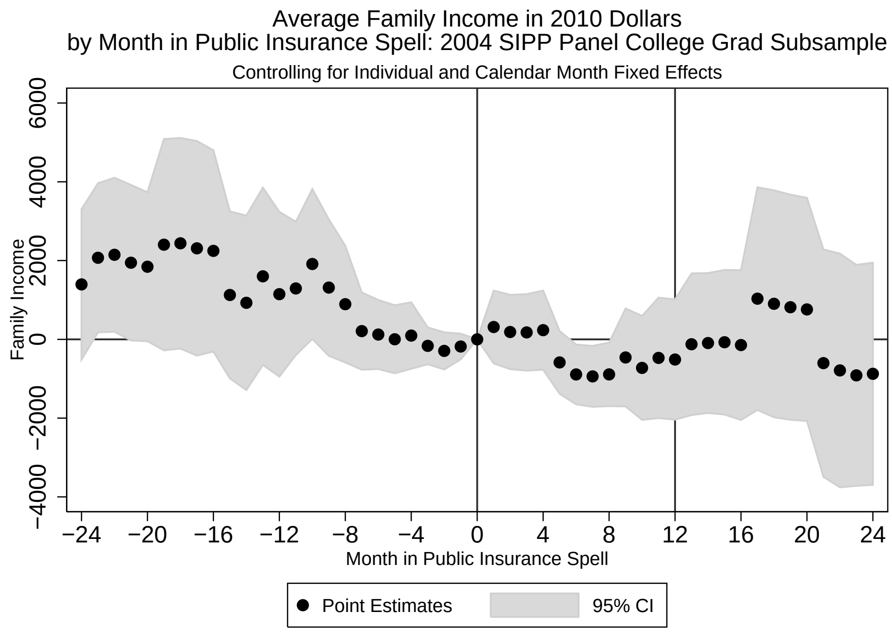
Figure 7: Average Family Income by Month in Medicaid Spell: Subsample with Construction-Worker Parents



Notes: Plotted are coefficients from regressions of family monthly income in 2010 dollars on a set of indicator variables for months before or since the start of a fresh Medicaid/CHIP spell for children whose parent worked in the construction industry during the sample period. The top panel plots the coefficients from the SIPP 2001 panel and the bottom plots those from the 2004 panel. The regression includes individual and calendar month fixed effects. The standard error is clustered at the SIPP sampling unit level. Month 0 (the month right before the start of a fresh Medicaid/CHIP spell) is the omitted category, and the corresponding coefficient is 0 by construction. The 2001 panel sample includes 321 fresh spells for 254 children from 120 sample units, and the 2004 panel sample includes 395 fresh spells for 359 children from 196 sample units. The sample is truncated by discarding the observations with Medicaid coverage before the start of a spell and those without Medicaid coverage after.

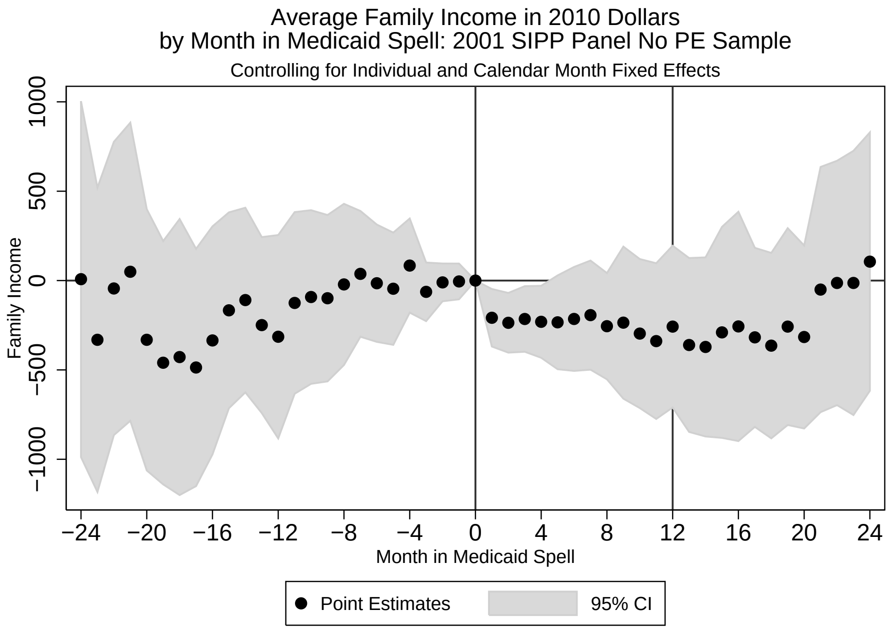
Figure 8: Average Family Income by Month in Medicaid Spell: Subsample with College-Grad Mother

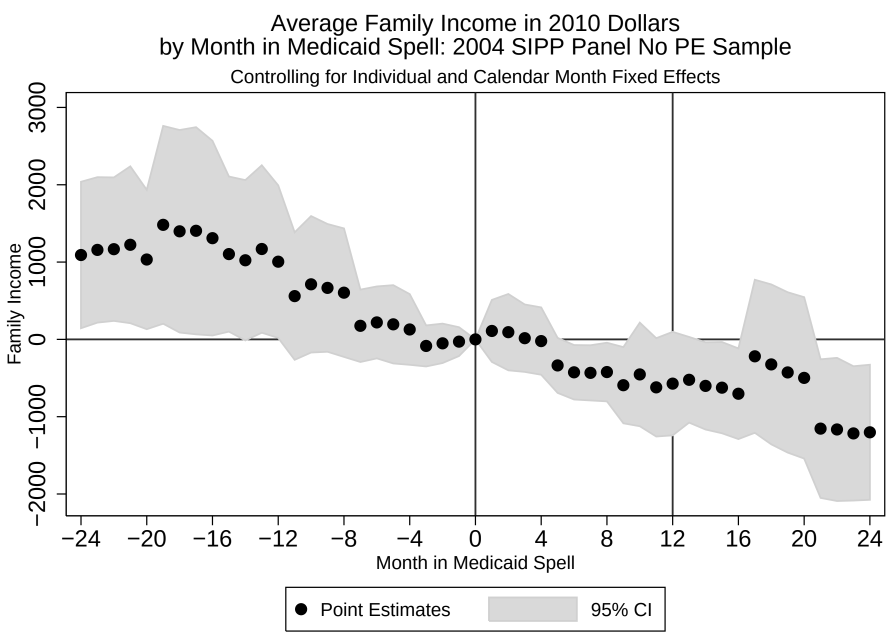




Notes: Plotted are coefficients from regressions of family monthly income in 2010 dollars on a set of indicator variables for months before or since the start of a fresh Medicaid/CHIP spell for children whose mother was a college graduate. The top panel plots the coefficients from the SIPP 2001 panel and the bottom plots those from the 2004 panel. The regression includes individual and calendar month fixed effects. The standard error is clustered at the SIPP sampling unit level. Month 0 (the month right before the start of a fresh Medicaid/CHIP spell) is the omitted category, and the corresponding coefficient is 0 by construction. The 2001 panel sample includes 472 fresh spells for 369 children from 237 sample units, and the 2004 panel sample includes 671 fresh spells for 614 children from 386 sample units. The sample is truncated by discarding the observations with Medicaid coverage before the start of a spell and those without Medicaid coverage after.

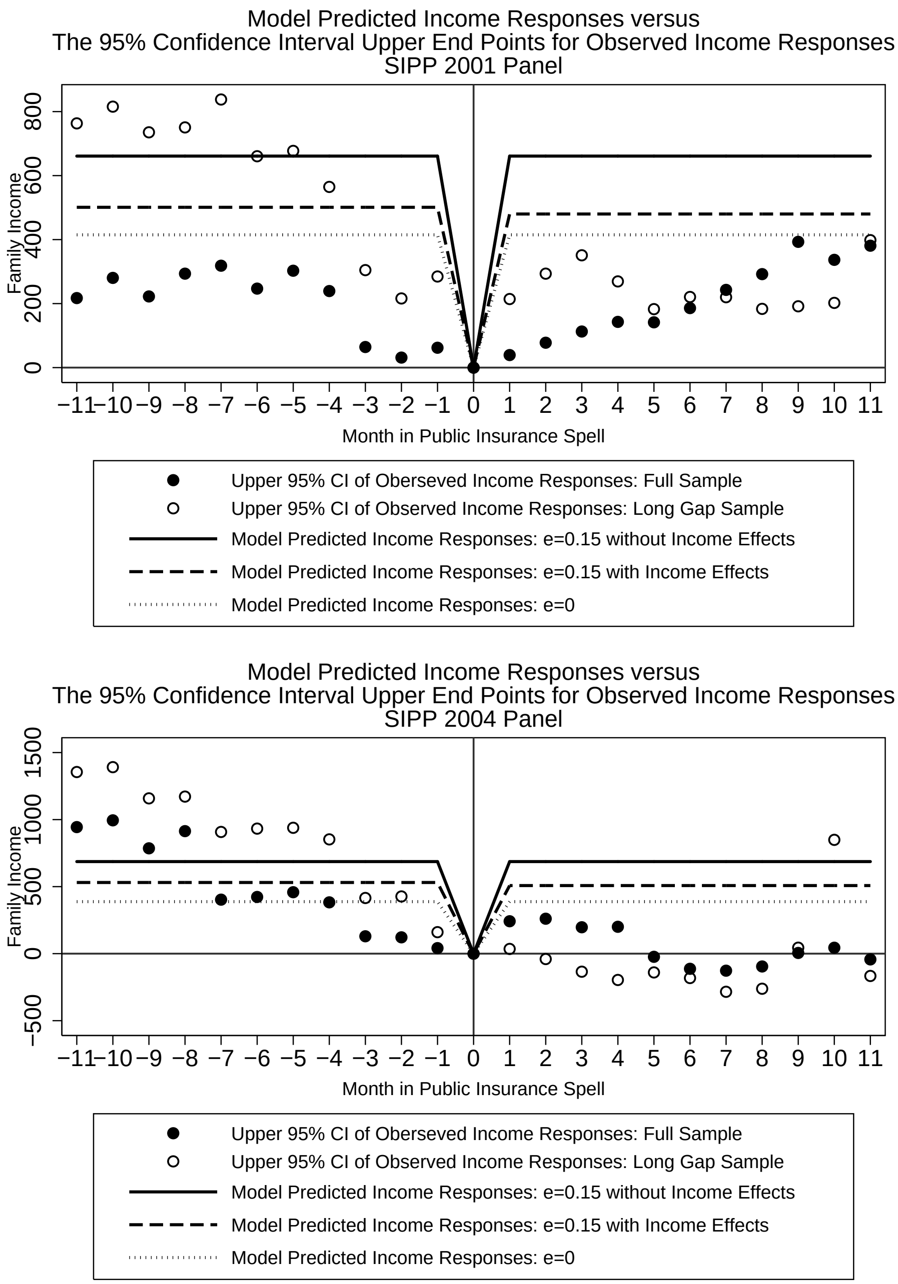
Figure 9: Average Family Income by Month in Medicaid Spell: Subsample with No-Presumptive-Eligibility States





Notes: Plotted are coefficients from regressions of family monthly income in 2010 dollars on a set of indicator variables for months before or since the start of a fresh Medicaid/CHIP spell for children living in states that do not offer presumptive eligibility to non-infants. The top panel plots the coefficients from the SIPP 2001 panel and the bottom plots those from the 2004 panel. The regression includes individual and calendar month fixed effects. The standard error is clustered at the SIPP sampling unit level. Month 0 (the month right before the start of a fresh Medicaid/CHIP spell) is the omitted category, and the corresponding coefficient is 0 by construction. The 2001 panel sample includes 1294 fresh spells for 993 children from 536 sample units, and the 2004 panel sample includes 1578 fresh spells for 1365 children from 787 sample units. The sample is truncated by discarding the observations with Medicaid coverage before the start of a spell and those without Medicaid coverage after.

Figure 10: 95% Confidence Interval Upper End Points for Observed Income Responses versus Model Predicted Income Responses



Notes: The top and bottom panels are graphical representations of Table 4 and Table 5 respectively. The solid dot, hollow dot, solid line and dashed line respectively represent columns (2), (4), (5) and (8), and the dotted line represents both column (7) and (10) in each of the two tables.