2015

Eligibility Recertification and Dynamic Opt-in Incentives in Income-tested Social Programs: Evidence from Medicaid/CHIP

Zhuan Pei
Cornell University

Upjohn Institute working paper ; 15-234

W.E. UPJOHN INSTITUTE
FOR EMPLOYMENT RESEARCH
Researching the causes and consequences of unemployment

Eligibility Recertification and Dynamic Opt-in Incentives in Income-tested Social Programs: Evidence from Medicaid/CHIP

Upjohn Institute Working Paper 15-234

Zhuan Pei
Cornell University
e-mail: zhuan.pei@cornell.edu

August 2015

ABSTRACT

Conventional labor supply studies assume constant eligibility monitoring of income-tested program participants, but this is not true for most programs. For example, states can allow children to enroll in Medicaid/CHIP for 12 months regardless of family income changes. A long recertification period reduces monitoring costs but is predicted to induce program participation by temporary income adjustments. However, I find little evidence of strategic behavior from the 2001 and 2004 Survey of Income and Program Participation. Given the lack of dynamic responses, I propose a framework to compute the optimal recertification period and find 12 months to be its lower bound.

JEL Classification Codes: I38, J20

Key Words: Labor supply, Medicaid, CHIP, continuous eligibility, recertification

Acknowledgments:

I am indebted to David S. Lee for his guidance and support. I thank the co-editor, two anonymous referees, Orley Ashenfelter, Rajh Chetty, Dong Beom Choi, Eleanor Choi, Hyun Soo Choi, Damon Clark, Janet Currie, Jo Duh, Hank Farber, Marjolaine Gauthier-Loiselle, Mike Geruso, Bo Honoré, Ilyana Kuziemko, Yan Lau, Nicholas Lawson, Lars Lefgren, Pauline Leung, Alex Mas, Jordan Matsudaira, Doug Miller, Tim Moore, Andrew Shepard, Lara Shore-Sheppard and seminar participants at APPAM, BLS, Brandeis, Brown, Mathematica, Princeton, Queen's Swarthmore, UIC, UIUC and the Upjohn Institute for helpful suggestions. I also Thank Rachel Licata at the Kaiser Family Foundation and Amy Steinweg and Becky Chenevert at the U.S. Census Bureau for answering my questions. Finally, I thank Carl Lieberman for outstanding research assistance. All errors are my own.

Eligibility Recertification and Dynamic Opt-in Incentives in Income-tested Social Programs: Evidence from Medicaid/CHIP*

Zhuan Pei†

Cornell University

First Draft: November 2011
This Draft: August, 2015

Abstract

Conventional labor supply studies assume constant eligibility monitoring of income-tested program participants, but this is not true for most programs. For example, states can allow children to enroll in Medicaid/CHIP for 12 months regardless of family income changes. A long recertification period reduces monitoring costs but is predicted to induce program participation by temporary income adjustments. However, I find little evidence of strategic behavior from the 2001 and 2004 Survey of Income and Program Participation. Given the lack of dynamic responses, I propose a framework to compute the optimal recertification period and find 12 months to be its lower bound.

JEL codes: I38, J20
Keywords: Labor Supply, Medicaid, CHIP, Continuous Eligibility, Recertification

*I am indebted to David S. Lee for his guidance and support. I thank the co-editor, two anonymous referees, Orley Ashenfelter, Raj Chetty, Dong Beom Choi, Eleanor Choi, Hyun Soo Choi, Damon Clark, Janet Currie, Jo Duh, Hank Farber, Marjolaine Gauthier-Loiselle, Mike Geruso, Bo Honoré, Ilyana Kuziemko, Yan Lau, Nicholas Lawson, Lars Lefgren, Pauline Leung, Alex Mas, Jordan Matsudaira, Doug Miller, Tim Moore, Andrew Shephard, Lara Shore-Sheppard and seminar participants at APPAM, BLS, Brandeis, Brown, Mathematica, Princeton, Queen's, Swarthmore, UIC, UIUC and the Upjohn Institute for helpful suggestions. I also thank Rachel Licata at the Kaiser Family Foundation and Amy Steinweg and Becky Chenevert at the U.S. Census Bureau for answering my questions. Finally, I thank Carl Lieberman for outstanding research assistance. All errors are my own.

†Department of Policy Analysis and Management, 134 Martha Van Rensselaer Hall, Cornell University, Ithaca, NY 14853. E-mail: zhuan.pei@cornell.edu

1 Introduction

An implicit assumption in labor supply studies of income-tested social programs is that program eligibility is being constantly monitored (e.g. Nichols and Zeckhauser (1982), Yelowitz (1995), Moffitt (2002)). However, this is not how many of these programs operate in practice today, and the time between two consecutive eligibility certifications, or the "recertification period", can be as long as a year. Although this policy lever is recognized and its effect on program participation explored in studies of transfer programs,[1] a formal theoretical and empirical investigation has not been carried out to address how program participants may respond to the incentives created by the *dynamic* budget constraint resulting from 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). The positive analysis of income and labor supply responses is key in answering the important normative question of how often eligibility monitoring should be conducted, the policy motivation of this study.

Uninterrupted eligibility monitoring ensures that an income-tested program is effectively 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". Granting continuous eligibility increases the value of a transfer program to its participants through two channels. The first channel is the reduction in transaction costs as pointed out by Currie and Grogger (2001) and Kabbani and Wilde (2003). The second – and rarely considered – channel is the change of a participant's budget constraint over time. If the nonlinearity in the budget constraint created by the eligibility requirements distorts a family's labor supply choices, the distortion is eliminated in any period in which eligibility is not checked, allowing the family to select a more optimal consumption bundle. Increasing the recertification period effectively decreases the number of periods in which a family faces the more stringent budget constraint, creating strong "dynamic opt-in incentives" for an otherwise ineligible family to participate in 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, the lengthening of

[1] Kornfeld (2002), Currie and Grogger (2001), Kabbani and Wilde (2003) and McKernan and Ratcliffe (2003) find that shortening the recertification period in Food Stamps reduces the participation rate. Staveley et al. (2002) and Ribar et al. (2008) find that exits from Food Stamps are much more likely in months of eligibility recertification. Prell (2008) treats income volatility as exogenous and discusses the optimal recertification frequency in the Women, Infants and Children (WIC) program.

the recertification period may *create* movements in the average income process around eligibility checks. These families that behave strategically – if they exist – are the "impostors" per Nichols and Zeckhauser (1982) in the dynamic context, and lowering the eligibility monitoring frequency decreases the cost of masquerading.

Setting the continuous eligibility period, therefore, involves the tradeoff between minimizing the number of impostors, who are not the intended beneficiaries of the program, and reducing the economic loss associated with monitoring. As mentioned above, the loss includes the administrative costs to the government, pecuniary and time costs of families participating in the program, and it also includes the deprivation of program benefits for some of the families most in need when the transaction costs of eligibility recertifications become too large (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 may reduce targeting efficiency as well. Given these tradeoffs, understanding the behavioral response to the lack of eligibility monitoring has important policy implications. The recertification period may be too long if extensive dips and rebounds in income are found. If no strategic behavior is found, on the other hand, the optimal eligibility recertification period can be computed by abstracting away from responses to the dynamic incentive.

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. 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 aforementioned strategic behavior, which then sheds light on the choice of the optimal continuous eligibility period. It should be pointed out that the incentives explored and the frameworks proposed in this study are not limited to public insurance for children: they also apply to other policy contexts such as cash welfare (TANF) and food assistance (SNAP and WIC) as well as several key features of the Affordable Care Act (ACA), which I discuss further in section 8.

The contributions of this paper are three-fold. First, I recognize the potential dynamic impact of a long continuous eligibility period on the labor supply decisions of program participants. I derive qualitative and quantitative predictions of the family income process using neoclassical labor supply models that incorporate the dynamic budget constraint. Second, I empirically examine the model predictions using data from the Survey of Income and Program Participation (SIPP). Third, I propose a simple framework to compute the optimal length of the continuous eligibility period for children on Medicaid/CHIP; the framework extends the work in Prell (2008), which studies the optimal recertification frequency in WIC, by removing the parametric restrictions on the income process, incorporating partial benefit take-up and allowing alternative social welfare formulations.

Empirically, I follow the event-study specification from Jacobson et al. (1993) and trace out the family income process over time as children enrolled in Medicaid/CHIP. The graphical analysis provides no strong evidence of income dip-and-rebound for families residing in states that provided 12 months of continuous eligibility, even in subsamples where it was most likely to occur. Formal statistical tests are conducted to compare the empirical rebound magnitudes to those calibrated using dynamic variants of the Saez (2010) model. The tests account for the SIPP seam bias, which blurs the timing of Medicaid/CHIP transition and dilutes the observed income responses, by adopting behavioral assumptions from Ham et al. (2009). By and large, the results of the tests reject the calibrated rebound magnitudes.

Comparisons of income processes between counterfactual groups are also carried out to address the issues of unaccounted income trends over a Medicaid/CHIP spell, concentration of strategic behavior in only a subset of the families, as well as possible model misspecification in the calibration exercise. I compare the income processes between (1) high and low income families and (2) families in states that did and did not provide 12 months of continuous of eligibility to simultaneously address all three issues above. Both comparisons follow a difference-in-differences type approach; in particular, a symmetric difference-in-differences strategy from Heckman and Robb (1985) and Ashenfelter and Card (1985) is adopted for comparison (1) to eliminate the biases created by the selection on and serial correlation in income. Statistical tests do not provide strong evidence that the groups in (1) and (2) have different income trends, underscoring the lack of strategic impostor behavior.

With no strong evidence supporting dynamic responses, I rely on the observed incomes in SIPP to compute the optimal monitoring frequency in a simple framework extending the textbook model of Salanie (2003). Under various functional forms of social welfare and assumptions regarding take-up rate, I derive mappings from the recertification cost parameters to the optimal monitoring frequency. For moderate costs, the calculation suggests that 12 months may serve as a lower bound on the length of the optimal continuous eligibility period.

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 providing continuous eligibility and to theoretically analyze families' responses to the provision. Section 4 describes the data used, and empirical results are presented in Section 5. Section 6 tests the labor supply theory by calibrating the dynamic variants of the Saez (2010) model and by carrying out counterfactual analyses. Section 7 investigates the optimal length of the continuous eligibility period. Section 8 outlines how the new ACA policies may affect dynamic incentives. Section 9 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, the aged, blind and the disabled. However, eligibility for public insurance through Medicaid has expanded substantially over time, particularly for dependent children.

Over the 1980s and 1990s, a series of legislative acts gradually severed the link between Medicaid and welfare for children. Two of the largest federal expansions were included in OBRA (Omnibus Budget Reconciliation Act) 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 federal poverty line (FPL). OBRA 1990 required states to cover children born after September 30, 1983 with family incomes below 100% of the FPL. The mandated minimum federal standards from the two expansions have remained until this day; since all children today were born after 1983, a child is eligible for Medicaid when her family income is below 100% of the FPL or 133% if she is under six (for a detailed account of the major Medicaid legislations by 1997, see Gruber (2003)).

The creation of the State Children's Health Insurance Program in 1997 has allowed many states to further expand their public insurance programs above these standards. Unlike Medicaid, SCHIP provides states with block grants to fund coverage for children and has by and large left the implementation of the program to the individual states. Consequently, state public insurance programs for children vary widely in their eligibility requirements. One particular feature of some state programs is a continuous eligibility period as permitted by the Balanced Budget Act of 1997, which provides eligible children with uninterrupted coverage for up to 12 months, regardless of whether their families' incomes rise above the eligibility threshold during this period. Table 1 lists the states by whether they provided 12 months of statutory continuous eligibility during 2000 and 2007, the time period underlying the empirical analysis of this study. For many of the states that did not provide 12 months of continuous eligibility, the recertification period is still 12 months but participating families are required to report changes in their circumstances soon after they occur.

Using aggregate administrative data from the Medicaid Statistical Information System (MSIS), Figure A.1 illustrates the impact of eligibility recertification period on children's Medicaid enrollment. In Washington and New Mexico, the two states that experienced a changes in recertification period in both directions, enrollment dwindled by about 10% in the year after the recertification period decreased from 12 months to six, but then bounced back in similar magnitudes after 12-month-recertification was reinstated. In SIPP data, the log-rank test provides strong statistical evidence (significant at the 0.01-level) that public insurance spells are longer in states with 12-month continuous eligibility compared to states with a 6-month renewal period.[2]

In most states, Medicaid and CHIP eligibility is established based on the most recent monthly income for wage-earning families, giving rise to the dynamic opt-in incentives. Table 2 summarizes the income proof requirements in states providing 12-month continuous eligibility, and the vast majority require one or multiple pay stubs from each job within a month of application. Toward the end of the benefit year, families need to have their incomes verified again in order to continue their children's coverage by public insurance. A package containing renewal materials is typically sent to the current beneficiaries some time before their coverage is scheduled to end. As seen from Table 2, however, the timing of this renewal process varies across states, which can start as long as three months or as short as two weeks before the benefit year is over; in a few of the states, it is the local offices that determine when to initiate the recertification process. Because of differences in the timing of renewal, the month in which a strategically behaving family dips its income in order to pass eligibility renewal may vary. Given this ambiguity, I will focus on the behavioral response at the time of the initial program enrollment.

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.[3] Presumptive eligibility is relevant to

[2]The states with a 6-month renewal period were AK, GA, MN, OR and TX.

[3]Presumptive eligibility to infants and pregnant women was granted a decade earlier by OBRA 1986.

the study at hand because children do not always need to meet the usual income requirements to receive public insurance coverage when it is granted. The states that provided presumptive eligibility to children in addition to allowing 12-month continuous eligibility between 2000 and 2007 are indicated in Table 2.

The last columns of Table 2 indicate whether the states have mandated a waiting period (three or six months) for children whose private insurance was voluntarily dropped before they were enrolled in CHIP. The intent of the waiting period is to mitigate the potential crowding-out of private insurance. Because the measure does not apply to Medicaid children nor to those who had not been enrolled in private insurance, however, the population it affects is likely to be small. Nevertheless, the existence of the waiting period still complicates the timing of the potential strategic behavior, and will be addressed in the empirical analyses.

In addition to the several eligibility measures mentioned above, state Medicaid programs differ on many other dimensions, such as the range of services covered, the quality of care enrollees receive, the reimbursement policies to health care providers, etc. According to the Medicaid program rankings by Ramirez de Arellano and Wolfe (2007), states that provide 12-month continuous eligibility (the first row of Table 1) rank somewhat lower overall in overall quality. The average ranking of the 12-month states are four to five places below the other states, suggesting that long continuous eligibility may serve as a substitute for other program features.

3 Theoretical Framework of Eligibility Recertification in Transfer Programs

Means testing in transfer programs reflects the government's redistributive taste and its intention to target the needy. If income does not change over time and those in need remain in need, 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 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. If monitoring eligibility is costless for both the government and the family, then the government should perform an eligibility check every period to ensure targeting efficiency, as 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 the non-needy.

It may be tempting to propose a long continuous eligibility period in the case of high administrative cost or low income volatility, but policymakers should also be wary of the potentially large labor supply distortions this may induce. 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 lifetime – families of all income levels face strong incentives to temporarily lower their income and participate in the program, which will render the system unsustainable. Therefore, understanding families' income and labor supply responses to the dynamic opt-in incentive is key in considering the optimal monitoring frequency. In subsection 3.1, I review the prediction of a class of standard static (i.e., assuming constant eligibility monitoring) neoclassical 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 family labor supply decisions when eligibility for Medicaid/CHIP is recertified every period. This is the standard assumption in the conventional labor supply literature, and it stipulates that families are eligible for benefits only if their income is below a cutoff. The implications of this assumption have been explored in other studies (e.g., Blank (1989) and Yelowitz (1995)). I review it here using the utility functional forms that are extensions of Saez (2010), because results derived below are relevant for the dynamic problem with continuous eligibility provision in section 3.2.

Consider the utility function

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

which increases with post-tax income (consumption) C and decreases with pre-tax income Z as in Saez (2010). Z can be thought of as an increasing function of hours worked H, and (1) can be alternatively formulated in terms of C and H. The utility function is written in Z as opposed to H because Z is better measured than H in the empirical analysis. The parameters ρ, n and e respectively indicate the curvature/risk aversion in consumption, the taste for work and the responsiveness of pre-tax income tax rate changes. For an agent facing the budget constraint $C = (1-t)Z$ with t being the tax rate, her optimal pre-tax income choice is $Z^* = (1-t)^{\frac{e-\rho e}{\rho e+1}} n^{\frac{1}{\rho e+1}}$.

To illustrate the roles of n and e, consider the special case of $\rho = 0$, which corresponds to the quasi-linear utility functional form of Saez (2010) and Chetty et al. (2011). The expression of the optimal pre-tax income simplifies to $Z^* = (1-t)^e n$. It follows that $Z^* = n$ when $t = 0$, and n can be interpreted as the income choice in the absence of tax and transfer programs in a quasi-linear framework. An agent with a larger n both works and consumes more, and n is assumed to be smoothly distributed across the population. In the quasi-linear case, the parameter e is the Marshallian elasticity of pre-tax income with respect to (one minus) the marginal tax rate: $\frac{(1-t)}{(Z^*)}\frac{d(Z^*)}{d(1-t)} = e$, and it can be shown that e is the Hicksian and Frisch elasticity as well. For the more general utility function of (1), e can only be interpreted as the Frisch elasticity of income/labor supply, which is convenient for the dynamic problem below.[4]

The existence of Medicaid/CHIP induces at least one discontinuity in the relationship between consumption and income. For simplicity of exposition, I include only one such notch and a single marginal tax rate in the presentation of this section.[5] When eligibility is checked every month, this budget constraint is static. It can be specified as

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

following Blank (1989) and Yelowitz (1995). The parameter γ is the Medicaid/CHIP eligibility cutoff, g the monthly value of public insurance, and t the marginal tax rate. As is well known in the literature, no family will choose income to be just above the threshold, and families with type n between two threshold values, n_γ and $\bar{n}$, would choose income γ and opt into the program. The lower threshold n_γ is the type of agent who would choose income γ absent the notch; the upper threshold $\bar{n}$ is the highest type of agent who would choose γ in the presence of the notch, and it delineates the program participants ($n \leqslant \bar{n}$) from non-participants ($n > \bar{n}$). It is straightforward to show that $n_\gamma = \gamma^{1+\rho e}(1-t)^{\rho e - e}$, and since a type-$\bar{n}$ agent 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 $((1-t)^{\frac{e+1}{\rho e+1}}\bar{n}^{\frac{1}{\rho e+1}}, (1-t)^{\frac{e-\rho e}{\rho e+1}}\bar{n}^{\frac{1}{\rho e+1}})$, $\bar{n}$ can be solved by equating the utility (1) evaluated at these two bundles. In the special case of $\rho = 0$, $\bar{n}$ is the solution to the simplified equation:

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

[4]The Marshallian elasticity of labor supply with respect to the marginal tax rate reduces to $\frac{\partial Z^*}{\partial(1-t)}\frac{1-t}{Z^*} = \frac{e-e\rho}{\rho e+1} < e$ when $\rho, e > 0$, whereas the Hicksian elasticity varies across agents. See MaCurdy (1981) and Browning et al. (1985) for discussions on the magnitudes of the three elasticities.

[5]Families enrolled in CHIP with income above the 150% FPL may be subject to moderate premiums and copayments, which implies a lower CHIP notch than that of Medicaid. The empirical impacts of the presence of other notches (induced by Medicaid or other transfer programs) are discussed in section 6.1.

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 may lower their labor supply and become eligible for program benefits. This distortion is well established in the literature, and it is robust to various extensions (allowing for discrete labor supply choices, heterogeneous elasticity and program participation cost) as shown in section A of the Supplemental Appendix.[6]

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 for a set of *dynamic* budget constraints as opposed to the static expression of (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. The formal treatment of the dynamic problem is provided in section B of the Supplemental Appendix, but the solution in a special case can be intuitively characterized.

Consider the model where the flow utility is quasi-linear, i.e. equation (1) with $\rho = 0$, and the continuous eligibility period τ is 2. Similar to $\bar{n}$ in the static case, a threshold type, denoted by $\bar{n}^d$, delineates program participants ($n \leqslant \bar{n}^d$) from non-participants ($n > n^d$) in the dynamic model. As shown in the Supplemental Appendix, $\bar{n}^d$ is determined by

$$\gamma(1-t) + (1+\beta)g - \frac{\bar{n}^d}{1+1/e}(\frac{\gamma}{\bar{n}^d})^{1+1/e} = \bar{n}^d(1-t)^{1+e} - \frac{\bar{n}^d}{1+1/e}(1-t)^{1+e} \tag{4}$$

where β is the discount rate.

The threshold types of $\bar{n}^d$ and n_γ ($n_\gamma = \frac{\gamma}{(1-t)^e}$ in the quasi-linear case) divide the population into three groups that behave differently. Agents with high n ($n > \bar{n}^d$) choose not to participate in the program and have constant income supply, agents with low n ($n \in (0, n_\gamma]$) participate and do not vary their income supply between the first and second periods, and agents in the middle ($n \in (n_\gamma, \bar{n}^d]$) lower their income initially to gain eligibility, but they revert back to their desired interior solution with an income above γ when their eligibility is not checked.

The left and right panels of Figure 1 provide graphical illustration of the solution to the static and dynamic models with quasi-linear utility, respectively. An $\bar{n}^d$-agent is indifferent between participating and not participating in a constantly-monitored program with benefit $(1+\beta)g$. In other words, doubling the

[6]The Supplemental Appendix is online at https://sites.google.com/site/peizhuan/files/Supplemental Appendix.pdf.

length of the recertification period induces the same agents to participate in the program as increasing the program benefit level from g to $(1+\beta)g$! It is easy to show that for a general recertification period τ, the size of the benefit notch an agent faces is effectively $\sum_{i=0}^{\tau-1}\beta^{\tau}g$, which is approximately τg when $\beta \approx 1$, when making her participation decision in month $s = 0$.

Under the general utility function (1), the solution may no longer be obtained analytically. But qualitatively speaking, once a new applicant family is approved for benefit, the transfer may reduce labor supply through income effects. This implies that the rebound in income after starting a public insurance spell will not be as large as when income effects are absent. In addition, the curvature puts pressure on agents to smooth consumption, and fewer agents choose to participate in the program as a result. While the addition of a borrowing/saving device to the model has no effect on the optimal income path in the quasi-linear case, the rebound can be shown to be stronger with the utility (1). In a nutshell, agents applying for benefits will borrow against the future to smooth consumption and consequently want to work more when their income choices are not constrained,[7] and omitting the borrowing/saving device from the model will lead to *conservative* predictions on the magnitudes of the dip and rebound.[8]

To summarize, the dynamic labor supply models make the prediction that average income drops at the income eligibility check and rebounds afterward. The magnitudes of the dip and rebound depend on the model parameters ρ and e. In the following sections, I will investigate whether families' empirical behaviors conform to the qualitative and quantitative predictions of the dynamic neoclassical models.

4 Data and the Construction of the Analysis Sample

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 the Survey of Income and Program Participation. SIPP is a representative household survey designed to provide detailed information on income dynamics and government program participation. Each of the panel files contains four rotation groups, only one of which is interviewed in a given calendar month. This means that each adult member of the participating household was interviewed every four months about his or her experiences since the last interview (the four-month interval is called the reference period, and the four months are referred to as reference month 1 to reference

[7] Few states mandated asset tests in determining children's eligibility for Medicaid/CHIP during the sample period. In 2007, for example, only South Carolina required the asset test among the states that provided 12-month continuous eligibility.

[8] The low-income families studied typically do not have much savings. However, as Scholz et al. (2006) show, the low savings rate may not be suboptimal, at least for an older population.

month 4). The two SIPP panels span the period from October 2000 to December 2003 and from October 2003 to December 2007 respectively. All four rotation groups in the 2001 panel provide information for 36 consecutive months, and those in the 2004 panel for 48 months.

The chief advantage of SIPP over other candidate data sets (CPS, PSID, HIS, etc.) is its panel structure at the monthly frequency and the rich array of variables on income, program participation and family structures. Since the focus of the study is to examine family income responses immediately before and during a child's Medicaid/CHIP spell, SIPP is the best choice among public use survey data sets. There are, however, several important limitations to the SIPP data.

The first limitation is the existence of the well-known seam bias, which refers to the fact that changes in income and program participation are *under*-reported *within* a single four-month reference period and *over*-reported *between* two reference periods (see Pischke (1995) and Ham et al. (2009)). For example, children's reported public insurance coverage spells are much more likely to start on reference month 1 than reference month 2, 3 or 4. In fact, about 83% of the fresh spells in the 2001 panel analysis sample and 91% of the fresh spells in the 2004 panel analysis sample start on the first month of the reference period. The seam bias dilutes the income responses, and I address it in section 6 by adopting the behavioral assumptions of Ham et al. (2009). Second, as is true with all survey data, Medicaid and CHIP coverages cannot be reliably distinguished.[9] 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. Third, identifiers of families in less populated states are missing from the 2001 panel. Families in Maine and Vermont share the same geographical identifier, and the state of residence for North Dakota, South Dakota and Wyoming families cannot be identified either. Because these states have different Medicaid/CHIP policy parameters, they are excluded from the analysis sample. Because of the larger sample size of the 2004 panel, all fifty states plus the District of Columbia have their own identifier, and therefore every state can be included.

The main analysis sample consists of children living in states providing 12-month continuous eligibility, who had started a public insurance spell during the SIPP panel. The reason for choosing children instead of families as observation units is that individuals can be tracked through the panel without ambiguity but the definition of a family may change. The restriction to "fresh" spells comes from the necessity of

[9]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 [affirmatively to] the question asked first, resulting in higher reported levels of CHIP than of Medicaid for Panel 2004)."

identifying the timing of benefit application, which is not possible with the left-truncated spells, which start with the child's first appearance in the panel. In addition, spells started by infants, by children who moved to another state[10] or by children on the Supplemental Security Income (SSI) program are excluded from the analysis sample. Infants are excluded because most states have been extending presumptive eligibility to infants since the 1990s; children whose families moved across states pose a challenge in the assignment of Medicaid/CHIP parameters; and children on the SSI program were conferred automatic eligibility for public insurance. As shown in Table 3, the analysis sample consists of 2582 and 2821 fresh public insurance spells for the 2001 and 2004 panels respectively.

Nuclear families for each child are constructed using information on the relationship to the household and family reference person (head). In the 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 typically used in the determination of eligibility for means-tested programs. Family-level variables are calculated by aggregating over individual family members, and family income includes earned and unearned incomes, excluding welfare receipt and children's incomes.[11]

Finally, 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 (2000-2011) 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.

Table 4 presents variable averages for both the 2001 and 2004 SIPP panels immediately before and during the first month of public insurance spells (spell month 0 and spell month 1 respectively). The 2001 and 2004 summary statistics are reasonably similar. On average, a child switched onto public insurance during a SIPP panel when she was between 8 and 9 years old. About half of the children were female, and around 20% were black. The average child lived in a four-person nuclear family, and 50% to 60% came from two-parent families. The vast majority of the families were working families – only around 10% did not have non-welfare income around the time their child started a public insurance spell and less than 5%

[10] I do include children who moved across states during the panel as long as the move did not occur during a public insurance spell. As a result, the fourth row of Panel (a) of Table 3 is the sum of the last three rows for columns 1 and 2, but not for columns 3-6.

[11] 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.

of the parents claimed unemployment benefits. Around 20% of the families were on Food Stamps, and less than 5% of the families received welfare cash transfers from TANF programs. The median family income in spell month 0 was just below $1900 in 2010 dollars for the 2001 panel and just below $2300 for the 2004 panel. In comparison, the spell-month-1 median income was slightly lower (1.5-2%) in both panels. In the next section, I will provide a description of the income processes over a much wider time window, while controlling for individual and time fixed effects and economic conditions.

5 Descriptive Analysis of Income and Labor Supply Responses

5.1 Empirical Specification and Full-sample Results

In this section, I present descriptive evidence on families' income responses over their children's Medicaid/CHIP spell. First, I follow a flexible event-study specification adopted by Jacobson et al. (1993), and estimate the fixed effect regression

$$Y_{it} = \omega_i + \lambda_t + \sum_{|k| \leqslant m} D_{it}^k \delta_k + X_{it}\beta + \varepsilon_{it} \tag{5}$$

where ω_i and λ_t are individual and calendar month fixed effects. k is the "spell month": $k = 1$ indicates the first month of public insurance coverage, and $k = 0$ the month immediately before coverage begins. D_{it}^k is a dummy variable, which takes the value of 1 if child i in calendar month t started her public insurance $(k-1)$ months earlier (or, if k is negative, child i began her coverage k months later). X_{it} is the unemployment rate of individual i's state in calendar month t. Spell month 0 is the omitted category in the regression. As a result, $\delta_0 = 0$ by construction, and δ_k measure the difference in the average outcome in spell month k relative to spell month 0.

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 or the last month of the panel, which render the estimation of δ_m and δ_{-m} imprecise for large m. Therefore, I set $m = 24$ and examine the income and labor supply responses 24 months before and after the beginning of a spell. Even though the sample period for $m = 24$ covers two recertifications, I will only focus on the initial entry of program participants as discussed in section 2, due to the variability in the renewal process and the resulting ambiguity in the timing of potential strategic behaviors.

As is evident from Table 3, some of the children in the analysis sample experience multiple public insurance spells. Since an event-study framework usually calls for single status transitions, each fresh spell is constructed such that it only contains a single transition from noncoverage to coverage. Specifically, let k^- denote the last month before spell month 0 ($k^- < 0$) in which the child was covered by public insurance, and let k^+ denote the first month after spell month 0 ($k^+ > 0$) in which the child switches off public insurance. For each fresh spell, I discard all observations before k^- and after k^+, which eliminates status transitions from coverage to noncoverage. All fresh spells constructed in this manner are included in the estimation of (5), and the clustering of standard errors at the individual level or higher accounts for the correlation in the outcome variables across multiple spells for the same child.

Figure 2 plots the movement of average family incomes, i.e. the estimates of the δ_k's from (5), over the 48 months around the beginning of a public insurance spell.[12] Both the point estimates and the point-wise 95% confidence intervals are shown, for which the standard errors are clustered at the SIPP variance stratum level.[13] Neither of the figures shows 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 practically flat; the average income increases gradually during the public insurance spell especially after 12 months, but the period immediately following the spell start shows no rebound. In the 2004 panel, the income process shows a persistent downward trend throughout the 4-year window without a visible rebound.

Unfortunately, SIPP does not collect information on hours worked at the monthly level but usual hours worked are reported for the entire wave (four months). Using this wave-frequency variable, however, clouds the model-predicted dip-and-rebound movements in the *immediate* months surrounding the spell start. Therefore, I describe the labor supply movement using a less precise variable than hours worked but at the monthly frequency. In particular, I construct a dummy variable indicating whether or not the head of the family – defined to be the 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 A.2. There is a downward trend for the two years before the spell start in both panels. The downward trend continues in the 2001 panel for

[12]The regression is weighted using the person weight at the beginning of a spell. Weighting has little impact on the empirical estimates.

[13]The primary sampling unit (PSU) and strata codes are not included in the SIPP public use data files due to confidentiality concerns. Instead, SIPP constructs variance units and strata, which are meant to be treated as PSUs and strata in variance estimations. There are 105 and 114 variance strata in the 2001 panel and 2004 panel full analysis sample, respectively. See Chapter 7 of Westat (2008) for details.

about six months, whereas it flattens out in the 2004 panel. As with the income processes in Figure 2, no salient rebound is present in the labor supply processes.

Even though the strategic behavior predicted by the labor supply model is not salient in the full sample, certain subgroups may be expected to exhibit stronger responses than others. Examining these subgroups separately may help to isolate the effects that are otherwise masked in the full sample. I carry out subsample analyses in the following subsection.

5.2 Subsample Analyses

In this subsection, I estimate (5) in numerous subsamples. A particular subsample is chosen for one of five reasons: (1) it allows for a lower degree of error in identifying a fresh public insurance spell, (2) it removes some of the ambiguities from other institutional provisions that complicate the incentives represented in the simple labor supply model, (3) it is easier for the families in the subsample to adjust their labor supply, (4) it consists of families more likely to understand program rules, or (5) the families in the subsample have a stronger incentive to behave strategically. As a result, I expect the strategic behavior to be more easily detected in the chosen subsamples.

Subsample 1 consists of children who report no public insurance coverage for 12 consecutive months before the start of a spell. The selection of this "long gap" sample follows the observation that many fresh spells are preceded by a short gap in public insurance coverage. Short coverage gaps are consistent with what is found using administrative data; for example, 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, the presence of short gaps before spell start does cause concern regarding the reliability of the identification of fresh spells. Although it is rare for families to report coverage while not covered by public insurance (Card et al. (2004)), the converse is more common, and the under-reporting of coverage at a particular month during a long spell will lead to the false identification of starting a fresh spell.[14] This measurement error problem is mitigated by restricting observations to the long gap sample. By virtue of its construction, subsample 1 consists mostly of single public insurance spells.

[14]The under-reporting of public insurance for dependent children is graphically represented in Figure SA.1. The number of dependent children on public insurance is first estimated using SIPP for every month between October 2000 and December 2007 and then compared to the administrative totals extracted from the MSIS. Figure SA.1 plots the administrative total from MSIS as well as the ratio of SIPP estimated total to administrative total. The under-reporting rates range between 10% and 25% for both SIPP panels (while gradually increasing within each panel), which are similar to those found using earlier or partial SIPP samples, e.g. Card et al. (2004) and Wheaton (2007). Public insurance under-reporting is also examined in the subsample of states providing 12-month continuous eligibility, and its patterns are very similar to those in Figure SA.1.

The next two subsamples are chosen to minimize interactions with other aspects of the Medicaid program and isolate the effect of the 12-month continuous eligibility provision. As mentioned in section 2, children in a presumptive eligibility state do not always need to meet the usual income requirements when receiving public insurance coverage, and the existence of a CHIP waiting period for children whose private insurance voluntarily dropped complicates the timing of the strategic behavior. Therefore, subsample 2 is restricted to children residing in states that neither provided presumptive eligibility nor mandated a CHIP waiting period in the sample period. The next subsample attempts to resolve the complications created by joint enrollment in parental Medicaid. Since adult Medicaid has shorter renewal periods and expected income change reporting, family income for children who transitioned into public insurance with their parents may not rebound much. Therefore, I exclude children whose parents took up Medicaid when they began their public insurance spell in subsample 3.

Subsamples 4 and 5 consist of children living in families that have more flexibility in adjusting their labor supply. Children in two-parent families form subsample 4 and those whose parents had worked in the construction or retail industries during the sample period constitute subsample 5. Two-parent families may be less credit-constrained and can shift their labor supplies more easily. Many jobs in the construction and retail industries are of a seasonal nature, and parents may time their government benefit application for when they do not work.

Children who have at least one college-educated parent are grouped in subsample 6. The expectation is that highly educated parent(s) may be more likely to understand program rules and the incentives therein. Finally, subsample 7 consists of children who have more than one child sibling. Public insurance is more valuable for families with more children, resulting in a stronger dynamic-opt-in incentive.

The sample sizes of the various subsamples are enumerated in Panel (b) of Table 3, and the income responses from the estimation of (5) are plotted in Figures A.3-A.9. A downward trend before the starting of a public insurance spell is visible in many of the figures, especially in the 2004 panel. The rebound after the spell start, however, is absent in all of the subsample figures, as is the case with the full sample. The income processes during the year after spell start are either flat or declining.

In summary, no strong descriptive evidence from SIPP 2001 and 2004 supports the income dip-and-rebound as predicted by the dynamic labor supply theory. This is true even in the various subsamples where strategic behavior – if it exists – should be more easily detected. However, strategic behavior may not be ruled out since it cannot be rejected that the δ_k's are positive for $k > 0$. In the next section, I investigate whether the empirical estimates are consistent with the *quantitative* theoretical predictions – formal tests are conducted by comparing the empirical rebound magnitudes to the calibrated model predictions.

6 Testing Model Predictions

6.1 Calibration of the Labor Supply Model

In this subsection, I calibrate the simple dynamic model from section 3 to benchmark the observed empirical income processes. The calibration exercise requires the assignment of sensible values or distributions to the set of parameters in the model: income supply elasticity e, consumption curvature ρ, discount factor β, taste/potential income n, public insurance eligibility threshold γ, value of public insurance g and marginal tax rate t. I present the calibration results under combinations of e, ρ and β that are commonly found in the empirical literature whereas the choices for the distributions of n, γ, g and t are data-driven.

Based on the state of residence, calendar year, family structure and family income of the observation, each family in the analysis sample is assigned a marginal tax rate t[15]. Recall that the optimal pretax income choice for a family with utility function (1) facing the budget constraint $C=(1-t)Z$ is $Z^*=(1-t)^{\frac{e-\rho e}{\rho e+1}}n^{\frac{1}{1+\rho e}}$. For each choice of ρ and e, therefore, I solve for the taste parameter of each child's family by $n=\frac{Z^*}{(1-t)^e}[(1-t)Z^*]^{\rho e}$ in the spirit of Brewer et al. (2010) where Z^* is the observed family income. Calculating n as such ignores the fact that some of the families in the calibration sample may be behaving strategically and that their Z^* is smaller than $(1-t)^{\frac{e-\rho e}{\rho e+1}}n^{\frac{1}{1+\rho e}}$. It follows that the n's for these families are underestimated, and the calibration exercise becomes conservative with a downward bias in the predicted dip-and-rebound magnitude.

For the program parameters, each child is assigned a CHIP eligibility threshold γ (the highest public insurance eligibility cutoff) given the state and year of the observation. g is taken to be the benefit notch associated with the CHIP program and is calibrated from the annual spending data. The spending data exclude beneficiary and third-party payments and reflect expected government subsidy, and using the considerably smaller CHIP notch as compared to its Medicaid counterpart[16] again renders the calibration exercise conservative. State-by-state spending-per-enrollee figures are not available for years earlier than 2004 from the

[15] Parents in a dual-headed family are assumed to file jointly and claim the deduction accordingly and that all families are assumed to claim standard deductions.

[16] 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.

Kaiser Foundation or the Center for Medicare and Medicaid Services. Therefore, I use the average per-enrollee spending for the entire U.S. as a measure of the notch, which grew 5% annually from \$835 in 2001 to \$1217 in 2007 in nominal terms. The monthly benefit amount per-child g_0 in a given year is $\frac{1}{12}$ of the annual per-enrollee spending that year, and the benefit notch g for that child's family is calculated as g_0 times the number of children therein.

For the remaining parameters of the model, the standard annual discount factor of 0.95 is used, which implies a monthly discount factor of $\beta = (0.95)^{1/12} = 0.996$. Three values for ρ and two for e are chosen to calibrate the model : $\rho = 0$, $\rho = 1.47$, $\rho = 4$, $e = 0$ and $e = 0.15$. As ρ increases, the predicted dip-and-rebound magnitude decreases largely because the desire to smooth consumption mitigates the dynamic opt-in incentives. The predicted income response goes up with e because larger labor supply elasticity makes families more responsive to non-smoothness in their budget constraint. Therefore, setting $\rho = 0$ gives the maximum income responses for any given e whereas letting e go to 0 gives the minimum income responses for any given ρ.[17] For the other two choices of ρ, 1.47 is the largest estimate from empirical micro studies using an additive utility function according to Chetty (2006), and 4 is the largest value used by Gruber (1997). As surveyed by Chetty (2012), 0.15 is the average Hicksian elasticity in the empirical micro literature for non-top income population.[18] Setting $e = 0.15$ is meant to present the range of income responses predicted by the model, but the focus will be on the case of $e = 0$, which deliver the minimum dip-and-rebound magnitudes.

Table 5 summarizes the calibration results, and the predicted income responses range from \$176 to \$285 in 2010 dollars for the 2001 panel. The predicted magnitudes are larger for the 2004 panel, reflecting higher family incomes in the analysis sample. As expected, the degree of income responses increases with e and decreases with ρ, and the rebound is smaller in magnitude than the dip for $\rho, e > 0$, due to the demand for more leisure as children in families acquire public insurance. It is an interesting feature of the model (1) that the income effect vanishes when e goes to 0, and the dip and rebound are again symmetric even when $\rho > 0$.[19]

[17]Different from a kinked budget constraint as in the case of Saez (2010), strategic behavior is expected in the presence of a notch even for the limiting case of $e = 0$.

[18]As mentioned in section 3, e is the Hicksian elasticity only in the quasi-linear model but is generally larger than the Hicksian elasticity with consumption curvature.

[19]Since $\lim_{e \to 0} u(C,Z) = \begin{cases} \frac{C^{1-\rho}}{1-\rho} & \text{if } Z \leqslant n \\ -\infty & \text{if} Z > n \end{cases}$, families with taste parameter n will choose $Z = n$ when the budget constraint is of the form $C = (1-t)Z + g$. The optimal Z does not decrease with g implying 0 income effect.

Formal statistical tests are carried out to examine whether the empirical rebound magnitudes are consistent with the model. A challenge in comparing observed and model-predicted income processes is the seam bias in the SIPP data mentioned in section 4. As explained in Pischke (1995) and Ham et al. (2009), seam bias is largely the result of the "telescoping behavior", meaning that survey respondents answer retrospective questions using their most recent income and program participation status. Seam bias leads to complications because it attenuates income responses even if every family behaves according to the model. As detailed in the Supplemental Appendix, I make seam-bias adjustment to the observed magnitudes of income rebounds by following two behavioral assumptions in Ham et al. (2009).[20] I then statistically compare the adjusted rebound magnitudes to the model prediction via bootstrap.[21]

The test results are summarized in Table 6. I present the seam-bias adjusted empirical rebound magnitudes as well as the p-values corresponding to different risk aversion parameters.[22] The average adjusted rebound magnitudes are negative in both the 2001 and 2004 SIPP panels and across all subsamples examined in section 5.2. For the 2001 panel, the models with $\rho = 0$ and $\rho = 1.47$ are rejected at the 0.05 level in all samples and that with $\rho = 4$ is rejected at the 0.05 level in most samples with the exception of subsamples 3 and 6; it is nevertheless rejected at the 0.1 level in these two subsamples. The adjusted average empirical rebound magnitudes are more negative in the 2004 panel, and all three models with $\rho = 0, 1.47, 4$ are rejected at the 0.01 level in every subsample.

There are several reasons why the calibrated rebound magnitudes may be underestimated, which makes the labor supply model even less consistent with the empirical income responses. First, because of the high income cutoff of CHIP, CHIP-eligible families may qualify for other programs 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 every state, the family will benefit from a more generous transfer by reducing their income to 133% of the FPL. At that level, the child will qualify for Medicaid in every state and enjoy more generous health care benefits. 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). Second, an extension of the model predicts that families will work more in the months in which they do not face eligibility certification if they are allowed to save and borrow intertemporally as noted in section

[20] To be concise, I only test the model using the rebound magnitude, since a lack of rebound rules out the strategic behavior predicted by the dynamic model.

[21] I calculate the calibrated model prediction in each bootstrap sample. The number of bootstrap repetitions is calculated based on Andrews and Buchinsky (2000).

[22] For brevity, the displayed p-values are only for tests of the zero-elasticity models, which are the hardest to reject.

3.2, leading to larger predicted rebound magnitudes. Third, as mentioned earlier in this subsection, the calculation of n ignores the fact that some families in the calibration sample may be behaving strategically and hence underestimates their rebound magnitudes. Given the statistical rejection of the conservatively predicted magnitudes, the evidence presented in this subsection provides little support for the neoclassical *dynamic* model.

6.2 Tests Using Counterfactual Groups

There are three issues with the calibration approach undertaken in the previous subsection. First, even though calendar month effects are controlled for in (5), there may also be spell month effects ξ_k that are common across individuals. It is impossible to distinguish ξ_k from the strategic income responses y_k in the estimation of (5) as δ_k is the sum of ξ_k and y_k, and a downward spell-time trend may mask a moderate y_k. Second, the calibration exercise would not reliably detect model-predicted rebounds if only a fraction of families had behaved strategically.[23] Third, an intensive-margin labor supply model is used to predict the rebound magnitudes, but the labor supply adjustments may be made along the extensive margin and imply different effect sizes from those in Table 5.[24]

In order to address these issues, I construct counterfactual groups which may share the same spell-time trend but are predicted to show different income responses by both the intensive- and extensive-margin labor supply models, even when only a fraction of families behaves strategically. The comparison between the treatment group and the counterfactual group, therefore, accounts for the spell-time trend, the presence of "never-takers" who would never behave strategically and is robust to the choice of labor supply model. The lack of differences between the treatment and counterfactual groups should strengthen the case against strategic behavior.

I conduct two counterfactual analyses in this subsection. The first comparison is between children in high and low income families in states providing 12-month continuous eligibility. Both the intensive- and extensive-margin labor supply models predict that the strategic behavior comes from families with an income above a certain threshold $\tilde{y}$ in the months before and after they apply for benefits. This implies that

[23]For example, some families may gain program eligibility by under-reporting their income. According to Hotz et al. (2002), there was substantial income under-reporting among ongoing cash welfare recipients. For Medicaid and CHIP, 3.1% of the cases were incorrectly assigned eligibility status per CMS (2014). Another example that encapsulates both the first and second issues is that public insurance enrollment may be triggered by a negative health shock. In this case, parents may have no intention of behaving strategically and may need to reduce work hours in order to care for the sick children.

[24]The calibration of the extensive-margin labor supply model requires identifying the joint distribution of the wage rates and tastes from the observed income distribution, which is beyond the scope of this paper.

the income process can be rewritten as

$$Y_{ik} = \omega_i + \sum_t D_{it}^k \lambda_t + (\xi_k + y_k \cdot H_i \cdot O_i) + \varepsilon_{ik}$$

where H_i indicates whether a child lives in a high-income family, and O_i indicates whether a family behaves strategically and opts into public insurance conditional on being high-income.[25] A simple approach is to divide the children into two groups based on whether their family income in spell month r ($r \neq 0$) is below or above $\tilde{y}$, and compare their income processes through the public insurance spell. The problem, however, is that families with a high (or low) month-r income tend to have a high (or low) transitory shock in month r, and the comparison of income processes between the two groups will be a biased estimate of the "intent-to-treat" income rebound magnitude due to serial correlation in the transitory shocks. This argument is well known in the program evaluation literature, and Heckman and Robb (1985) and Ashenfelter and Card (1985) have proposed the symmetric difference-in-differences estimator to eliminate the bias.

I adapt their strategy for the problem at hand for the case of $r = 4$. The reason for choosing this case along with the implementation details are in the Supplemental Appendix section D. The point estimates and p-values from estimating the symmetric difference-in-differences parameter, SDD_4, are presented in the first row of Table 7. Even though the point estimates for the 2001 panel are just below \$700, a large magnitude in light of the calibration exercise, the failures to reject the null hypothesis of $SDD_4 = 0$ (p around 0.2) show no strong evidence in favor of strategic behavior. In the 2004 panel, the point estimate is negative, and the statistical tests provide even less support of the labor supply models. Overall, the evidence from comparisons of income groups does not indicate strategic behavior.

The second counterfactual group consists of children living in states that did not provide 12-month continuous eligibility, i.e. states in the second row of Table 1. As mentioned in section 2, many of the states on this list allow a 12-month renewal interval, but families are required to report income changes when their children are covered by public insurance. To the extent that income change reporting is enforced in these states, the difference between the average rebound magnitudes from states with and without the continuous eligibility provision, denoted by $E_{CE}[\Delta Y_k]$ and $E_{NCE}[\Delta Y_k]$ respectively, should identify strategic behavior provided that families in the two sets of states share the same spell-month trend ξ_k.[26]

[25] This representation is equivalent to (5) with $\delta_k = \xi_k + y_k \cdot H_i \cdot O_i$. For simplicity, state unemployment rates are not an explanatory variable in this subsection, since it is both statistically and economically insignificant from the estimation of (5) in section 5.

[26] A caveat is that different continuous eligibility provisions may induce compositional differences in the participant pools across

The results from comparing the two sets of states are summarized graphically in Figure 3 and numerically in the second row of Table 7. In effect, equation (5) is estimated separately for the two sets of states, and Figure 3 plots the differences in the estimated δ_k's.[27] There is a very slight upward trend in the two-year window around the beginning of public insurance spells in the 2001 panel, but the pointwise 95% confidence intervals all include 0. The trend is essentially flat in the 2004 panel. To formally test whether the difference in the rebound magnitude is 0, I adopt the assumptions and method used in section 6.1 to account for the seam bias, and the resulting estimand is denoted by Δy^{emp}. As shown in Table 7, the point estimate of Δy^{emp} is 287 dollars in the 2001 panel but is not significant at the 5% level. The 2004 point estimate is quite negative, providing no indication that the families in the continuous eligibility states had a larger income rebound.[28]

To summarize, the counterfactual analyses comparing high and low income families and across states with different continuous eligibility provisions do not provide compelling evidence of families responding dynamically to continuous eligibility. The absence of labor supply response is consistent with Meyer and Rosenbaum (2001) and Ham and Shore-Sheppard (2005), but stands in contrast to the recent study of Garthwaite et al. (2014), who find a large labor supply response following the loss of Medicaid coverage in Tennessee. The findings in this paper may be explained by factors such as the lack of knowledge of program rules and frictions in income adjustments. Perhaps the best approach to identify the reason for the finding is a survey targeting the program beneficiaries.

It could also be the case that the counterfactual analyses are underpowered to detect dynamic responses due to small sample sizes and measurement issues with the SIPP data. The power of the statistical tests will be especially low if a large fraction of Medicaid enrollment was triggered by a negative health shock.[29] Testing the dynamic model may warrant another try with higher-quality data (e.g. linked administrative wage and program participation data). For this paper, however, I will compute the optimal recertification frequency while ignoring the dynamic labor supply implications.

the two groups of states, which may violate the common ξ_k assumption.

[27]For the results presented in the paper, calendar month effects are constrained to be the same across the two sets of states. Allowing the calendar month effects to differ has little effect on the estimates.

[28]There is even less evidence for a rebound when the comparison is made to states with an explicit six-month renewal period. The rebound differential is negative in both the 2001 and 2004 panels, and the associated p-values are 0.96 and 0.61, respectively.

[29]Because the trigger for Medicaid/CHIP participation is sometimes different from other social programs, e.g., cash welfare and food stamps, the lack of dynamic labor supply responses found in this paper may not generalize to other programs.

7 Optimal Length of the Continuous Eligibility Period

The social welfare function for determining the optimal transfer policy 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 an eligibility check is performed every month, when the take-up rate is 100% and when eligibility monitoring is free, the per-period social welfare is given by:

$$\underbrace{\int \Psi(u(C(z^*)))f_{Z^*}(z^*)dz^*}_{W} + \omega \underbrace{[R - \Pr(Z^* \leqslant \gamma)g]}_{S} \tag{6}$$

$$\text{s.t.} \quad C(z^*) = [(1-t)z^* + g]1_{[z^* \leqslant \gamma]} + (1-t)z^* 1_{[z^* > \gamma]}$$

Z^* denotes the pre-tax income choice of a randomly selected family, and its p.d.f. and c.d.f. are denoted by f_{Z^*} and F_{Z^*}, respectively. z^* is the realized value of Z^*, and $C(z^*)$ is the post-tax income of the said family.[30] 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 predetermined marginal tax rates on income. The government collects per-agent revenue R, which may contain income tax revenue $\int tz^* f_{Z^*}(z^*)dz^*$ as well as sources not explicitly modeled here,[31] and it is assumed that R is sufficiently large to cover program spending: $R \gg \Pr(Z^* \leqslant \gamma)g$.

In the social welfare formulation (6), public health insurance is modeled as consumption. It reduces out-of-pocket health care expenditure and allows families to spend the money elsewhere. Unlike in Finkelstein et al. (2015), the framework here does not explicitly incorporate health into the utility function. To the extent that Medicaid increases preventative care utilization (Currie and Gruber (1996)) and that it has positive long-term health consequences (Meyer and Wherry (2012)), the benefit of extending public insurance coverage is likely to be understated by using (6). Consequently, the resulting optimal recertification period may be biased downward.[32]

[30] In this section, the observed Z^* encapsulates the family's response to the static budget constraint via either the intensive or the extensive margin. The only requirement for the subsequent normative exercise is that Z^* does not respond to the dynamic budget constraint involving eligibility recertification.

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

[32] Section E.1 in the Supplemental Appendix provides further discussion of the social welfare function on how it extends the textbook formulation of Salanie (2003).

The evaluation of the optimal recertification frequency calls for a multi-period extension of the baseline formulation (6). 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 three months, a family is assumed to automatically participate in the program in months 2 and 3 if it participated in the program in period 1. In month 4, when the family's eligibility is recertified, the participation status will depend on whether its income for the previous month falls below the threshold. Formally, the social welfare function becomes

$$\begin{aligned} &\sum_{m=1}^{T} E[\Psi(u(C_m - \phi I_m))] - \omega E[R - (gP_m + \kappa I_m)] \\ \text{s.t.} \quad & C_m = [(1-t)Z_m^* + g]P_m + (1-t)Z_m^*(1-P_m) \end{aligned} \tag{7}$$

The expectation is taken over the joint distribution of $\{Z_1^*, ...Z_T^*\}$; P_m and I_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 frequency as illustrated above. In addition to spending on public insurance benefits, each eligibility check costs the government and the participating family κ and ϕ, respectively.

The optimal continuous eligibility period τ is obtained by comparing numerically calculated social welfare corresponding to different recertification periods, while taking tax rate t and eligibility cutoff γ as given. The joint distribution of $\{Z_1^*, ...Z_T^*\}$ is simply the observed empirical income distribution for families with at least a child who had appeared in all months in the 2001 and 2004 panels of SIPP ($T = 36$ and $T = 48$ for the two panels respectively).[33] Assuming 100% benefit take-up, I can impute each family's monthly program participation decision based on its income history or a particular recertification period τ, and calculate its consumption accordingly.

The remaining missing piece is 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 (6) where the cost of eligibility certification is zero. That is, the government abstracts away from the monitoring problem in determining the eligibility cutoff. Since ω will be smaller when monitoring cost is taken into

[33] This restriction leaves out certain families who gave birth during the panel. However, the family will be in the sample if the newborn has an older sibling who appears in all panel months.

consideration: $\omega = \{\Psi([(1-t)\gamma + g - \phi]) - \Psi([(1-t)\gamma])\}/(g+\kappa)$, the computed optimal τ should be considered as a lower bound. I can then solve for ω following the first order condition of γ as

$$\omega = \{\Psi((1-t)\gamma + g) - \Psi((1-t)\gamma)\}/g \tag{8}$$

where individual utility u is assumed to be linear in consumption, and $\Psi(u) = \frac{u^{1-\eta}}{1-\eta}$ is used for the weighting function under various values of η. 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. The resulting values of ω are very similar in the 2001 and 2004 panels and they decrease η goes up.

Welfare is computed for values of τ between 1 and 35, the latter of which is one less than the total number of months in the SIPP 2001 panel (since the previous month's income is used to determine eligibility, the maximum number of months a child can be covered during the 2001 panel is 35 months). The median hourly wage rate for government program interviewers, which is around \$19 in May 2010 according to the Occupational Employment Statistics database of the Bureau of Labor Statistics, serves as the basis for the value choices of κ (Irvin et al. (2001) adopt the same strategy[34]; Prell (2008) also includes overhead costs in estimating κ, which results in larger estimates and will consequently lead to a longer optimal τ if applied to my simulations[35]). It is more difficult to choose the values for ϕ for the numerical exercise, so the same values used for κ are used for ϕ out of 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.

Table 8 presents the optimal length of the continuous eligibility period from simulations under nine combinations of κ and ϕ (three values for both κ and ϕ), for $\eta = 1$[36] and assuming full take-up. The first row confirms the intuition that the government should certify eligibility every period when it is costless to do so and should check less frequently as costs increase. An increase in the cost on families, ϕ, is more likely to lengthen the recertification period than an increase in κ of the same magnitude. The optimal τ's computed from the 2004 panel are generally similar to but are somewhat larger than their 2001 counterparts. The estimates from both panels point to an optimal τ of 12 months or longer when ϕ exceeds \$19. More results

[34] 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 from CA, MI, MO and NJ between 1994 and 1995.

[35] See section E.3 for a comparison of the framework and results here to those of Prell (2008).

[36] When $\eta = 1$, Ψ reduces to the log function, which is the social welfare formulation used in Brewer et al. (2010).

are presented in the Supplemental Appendix Table SA.1 from the optimal calculation under different social welfare functions and more recertification cost parameter values. The numerical exercise is also carried out by relaxing the 100% take-up assumption. Under partial take-up, the optimal recertification periods turn out to be longer. When ϕ exceeds \$19 and $\eta = 1$, the implied continuous eligibility is around 20 months for the 2001 panel and above 20 months for the 2004 panel. This is because short recertification intervals tend to result in coverage gaps, leading to significant welfare losses for low-income families. In summary, the results suggest that 12 months serve as a lower bound of the optimal length of the continuous eligibility period for Medicaid/CHIP under reasonable parameter values.

There are a few caveats in interpreting the results in Tables 8 and SA.1. First, the calculations heavily depend on the assumed social welfare functions, take-up behavior and the assumed parameter values. Second, given that the simulation sample consists of families with at least a child that had nonmissing information for all interview months, their income processes may be different from those not included in the sample.[37] Third, an implicit assumption in calculating the optimal τ is that lengthening the recertification period does not induce dynamic labor supply behavior nor does it change the take-up probability among eligible families. As τ becomes very large, it is likely that the information regarding the program becomes more salient, more eligible families may choose to participate, and that ineligible families start responding to the dynamic incentives. On the other hand, even when the average monitoring costs are very low, having a small τ may asymmetrically lower the take-up rate among the most vulnerable.[38] Fourth, other aspects of the Medicaid program are assumed to remain the same in the normative exercise above, but this may not be the case if states tradeoff other program features with continuous eligibility, as discussed in section 2. If, for example, access to care is reduced in exchange for extending continuous eligibility, the optimal results are biased upward. Finally, while the framework can be used to analyze eligibility recertification in other welfare programs, the finding of the 12-month lower bound on continuous eligibility may not apply, due to differences in participant composition.

[37] I describe additional normative analyses Supplemental Appendix section E.2. Overall, the results do not appear to be very sensitive to alternative sample restrictions.

[38] As shown in Currie and Grogger (2001), single-parent families – arguably the more needy – disproportionately dropped out of Food Stamps during times when the frequency of recertifications had increased.

8 Eligibility Recertification and Dynamic Incentives under the Affordable Care Act

The landscape of American health care is rapidly changing after the passage of the Affordable Care Act. Key provisions of the ACA include expansions of public insurance, the establishment of a health insurance marketplace, subsidized private insurance coverage and individual and employer mandates. In this section, we outline how the ACA policies affect the dynamic incentives described in this paper.

For families with children on Medicaid/CHIP, the focus of this paper, the dynamic labor supply incentives are still present. The ACA still allows states the option to provide 12-month continuous eligibility to children on Medicaid and CHIP, and twenty-three states currently do so for both programs (CMS (2015a)).[39] However, two factors may change the effective size of the Medicaid notch for each family and therefore impact the extent of the strategic behavior empirically. First, families who disqualify for Medicaid are now eligible to receive subsidized private coverage through the marketplace, in the form of premium tax credits and reduced cost sharing. Consequently, the net value of Medicaid becomes lower for some families who would have chosen to dynamically opt into the program. On the other hand, the individual mandate may induce families with low expected health expenditure, who may not have otherwise had insurance, to (temporarily) lower their income and enroll in Medicaid, which is their least expensive option.

Furthermore, the dynamic incentives may also be relevant for participant groups other than children. A major component of the ACA is to incentivize the expansion of Medicaid eligibility to adults with income up to 138% of the FPL, which 31 states have already adopted. The group most affected by the expansion consists of childless adults, who were previously Medicaid ineligible. Continuous eligibility is currently not allowed and income change reporting is required for adults (see 42 CFR, Sec. 435.916). If enforcing accurate change reporting is difficult in practice, however, the availability of Medicaid for low-income adults may induce strategic dynamic behavior. It is unclear whether the childless adults are more or less likely to respond to the dynamic incentives than families with children. On the one hand, Garthwaite et al. (2014) find that childless adults exhibited large labor supply responses to losing health insurance coverage in Tennessee. On the other hand, Baicker et al. (2014) find a small and statistically insignificant reduction in labor supply

[39] Although eligibility for both the market-place health insurance plans and Medicaid is based on the modified adjusted gross income, which uses the annual income measure reported on tax returns, recent changes in income are reflected in determining Medicaid eligibility. In fact, Medicaid applicants can still submit pay stubs as proof of their recent monthly income, according to CMS (2015b).

after childless adults in Oregon were granted Medicaid eligibility.

As highlighted in section 7, the presence and magnitude of strategic dynamic behavior is only one component in determining the optimal eligibility redetermination frequency. The costs associated with eligibility redetermination (κ and ϕ for the government and participants, respectively) and income volatility also play an important role. As pointed out by Sommers and Rosenbaum (2011), both κ and ϕ may become larger post-ACA. Ineligibility in Medicaid may trigger enrollment in subsidized insurance plans, and since the participant will be first disenrolled from Medicaid and then enrolled in a different plan, more government resources may be required than pre-ACA. To the extent that the health care providers differ for Medicaid and subsidized private plans, participants may also incur significant cost if they are forced to switch. For income volatility, both Sommers and Rosenbaum (2011) and Shore-Sheppard (Forthcoming) document extensive income fluctuation across the Medicaid income cutoff, which may call for more frequent eligibility recertifications. Ultimately, the optimal recertification frequency for expanded Medicaid under the ACA should balance these various factors.

Finally, the issue of eligibility recertification may also be relevant for other components of the ACA. Specifically, families not eligible for Medicaid but with income between 100% and 250% of the FPL are eligible for lower copay, lower deductibles and premium tax credit on a sliding scale. Families with income between 250% and 400% of the FPL no longer qualify for copay and deductible subsidies but can still receive premium tax credit. The amount of premium tax credit is calculated based on annual income at tax filing. Therefore, it does not generate the same dynamic incentives as Medicaid.[40] Cost sharing subsidies (e.g. lower copay and deductible plans), however, are determined based on estimated income at the time of application. It is important to note these subsidies will not be lost if the participant's income rises above 250% of the FPL (Kaiser (2015)). Therefore, the dynamic incentives may be stronger for families with high expected medical expenses.

9 Conclusion

This paper presents both a positive and a normative analysis regarding eligibility recertification 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 participants in public insurance. Neoclas-

[40] Premium tax credit can be paid in advance based on estimated annual income, but any discrepancy between the estimated and actual premium tax credit a family is eligible for is reconciled when the family files for taxes the following year.

sical 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-income bundle. Using the 2001 and 2004 panels from SIPP, I adopt the Jacobson et al. (1993) event study framework to trace out the income and labor supply processes for families participating in Medicaid/CHIP. The point estimates in the full analysis sample and various subsamples in which strategic behavior is more likely to occur do not indicate the model-predicted dip-and-rebound pattern around the time a child gains public insurance coverage. Dynamic extensions of the Saez (2010) model 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 while accounting for the seam bias in the SIPP data rejects the intensive-margin dynamic model in most subsamples. In addition, I adopt a difference-in-differences type approach to compare the income processes between children in high and low income families and children living in states with different continuous eligibility provisions. The lack of differences in the two counterfactual analyses also does not support the strategic behavior predicted by the dynamic labor supply models.

With the positive analysis suggesting little evidence of dynamic response, I propose a framework to answer the normative question of 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 various functional forms of social welfare and assumptions governing benefit take-up. Under moderate cost parameter values, I find that 12 months is a lower bound of the optimal length of the continuous eligibility period for Medicaid and CHIP. Although this conclusion may be different given the recent significant changes in health care resulting from the ACA, the dynamic incentives examined in this paper still apply and remain to be explored in future research.

References

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

Andrews, Donald W. K. and Moshe Buchinsky, "A Three-step Method for Choosing the Number of Bootstrap Repetitions," *Econometrica*, 2000, *68(1)*, 23–51.

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

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

Baicker, Katherine, Amy Finkelstein, Jae Song, and Sarah Taubman, "The Impact of Medicaid on Labor Market Activity and Program Participation: Evidence from the Oregon Health Insurance Experiment," *American Economic Review*, 2014, *104(5)* (5), 322–328.

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

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

Blinder, Alan S. and Harvey S. Rosen, "Notches," *American Economic Review*, 1985, *75(4)*, 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)*, 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," *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*, May 2012, *80(3)*, 969–1018.

_ **, 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, "Medicaid and CHIP 2014 Improper Payments Report," Technical Report, Center for Medicare and Medicaid Services 2014.

_ , "Continuous Eligibility for Medicaid and CHIP Coverage," http://www.medicaid.gov/medicaid-chip-program-information/by-topics/outreach-and-enrollment/continuous.html August 2015.

—, "How Do I Resolve an Inconsistency?," https://www.healthcare.gov/help/how-do-i-resolve-an-inconsistency/ August 2015.

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

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

— **and Jonathan Gruber**, "Health Insurance Eligibility, Utilization of Medical care, and Child Health," *Quarterly Journal of Economics*, 1996, *111(2)*, 431–466.

de Arellano, Annette B. Ramirez and Sidney M. Wolfe, "Unsettling Scores: a Ranking of State Medicaid Programs," Technical Report, Public Citizen Health Research Group 2007.

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

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

Finkelstein, Amy, Nathaniel Hendren, and Erzo F. P. Luttmer, "The Value of Medicaid: Interpreting Results from the Oregon Health Insurance Experiment," June 2015.

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

Garthwaite, Craig, Tal Gross, and Matthew J. Notowidigdo, "Public Health Insurance, Labor Supply, and Employment Lock," *Quarterly Journal of Economics*, 2014, *129* (2), 653–696.

Gruber, Jonathan, "The Consumption Smoothing Benefits of Unemployment Insurance," *American Economic Review*, 1997, *87(1)*, 192–205.

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

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

— **and Lara Shore-Sheppard**, "The effect of Medicaid expansions for low-income children on Medicaid participation and private insurance coverage: evidence from the SIPP," *Journal of Public Economics*, 2005, *89* (1), 57 – 83. Tax and Transfer Programs for Low-Income People.

— **, 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.

Heckman, James J. and Richard Robb, "Alternative Methods for Evaluating the Impact of Interventions: An Overview," *Journal of Econometrics*, 1985, *30*, 239–267.

Hotz, V. Joseph, Charles H. Mullin, and John Karl Scholz, "The Effects of Welfare Reform on Employment and Income: Evidence from California," Technical Report 2002.

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)*, 685–709.

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

Kahn, Shulamit and Kevin Lang, "The Effect of Hours Constraints on Labor Supply Estimates," *Review of Economics and Statistics*, 1991, *73(4)*, 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 2000-2011.

— , "Health Reform FAQs," http://kff.org/health-reform/faq/health-reform-frequently-asked-questions/ August 2015.

Kenney, Genevieve, Victoria Lynch, Jennifer Haley, Michael Huntress, Dean Resnick, and Christine Coyer, "Gaines for Children: Increased Participation in Medicaid and CHIP in 2009," Technical Report, Urban Institute 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)*, 1059–1085.

McKernan, Signe-Mary and Caroline Ratcliffe, "Employment Factors Influencing Food Stamp Program Participation," Technical Report E-FAN Report No. 0-012, U.S. Department of Agriculture, June 2003.

Meyer, Bruce D. and Dan T. Rosenbaum, "Welfare, the Earned Income Tax Credit, and the Labor Supply of Single Mothers," *Quarterly Journal of Economics*, 2001, *116(3)*, 1063–1114.

— **and Laura R. Wherry**, "Saving Teens: Using a Policy Discontinuity to Estimate the Effects of Medicaid Eligibility.," Technical Report No. 18309, NBER Working Paper 2012.

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

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

Moffitt, Robert A., "Welfare Programs and Labor Supply," in A.J. Auerbach and M. Feldstein, eds., *Handbook of Public Economics*, Vol. 4, Elsevier, 2002, chapter 34.

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)*, 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)*, 805–840.

Prell, Mark A., "Income Volatility and Certification Duration for WIC Children," in Dean Jollifee and James P. Ziliak, eds., *Income Volatility and Food Assistance in the United States*, W. E. Upjohn Institute for Employment Research, 2008, chapter 9.

Ribar, David C., Marilyn Edelhoch, and Qiduan Liu, "Watching the Clocks: The Role of Food Stamp Recertification and TANF Time Limits in Caseload Dynamics," *Journal of Human Resources*, 2008, *43(1)*, 208–239.

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*, MIT Press, 2003.

Scholz, John Karl, Ananth Seshadri, and Surachai Khitatrakun, "Are Americans Saving "Optimally" for Retirement?," *Journal of Political Economy*, 2006, *114* (4), 607–643.

Shore-Sheppard, Lara D., "Income Dynamics and the Affordable Care Act," *Health Services Research*, Forthcoming.

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

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

Sommers, Benjamin D. and Sara Rosenbaum, "Issues in Health Reform: How Changes in Eligibility May Move Millions Back and Forth between Medicaid and Insurance Exchanges," *Health Affairs*, 2011, *30(2)*, 228–236.

Staveley, Jane, David Stevens, and Parke Wilde, "The Dynamics of Food Stamp Program Entry and Exit in Maryland," Technical Report, University of Baltimore August 2002.

Westat, "Survey of Income and Program Participation Users' Guide," Technical Report, U.S. Census Bureau 2008.

Wheaton, Laura, “Undersreporting of Means-Tested Transfer Programs in teh CPS and SIPP,” *Proceedings of the American Statistical Association*, 2007, *Social Statistics Section*, 3622–3629.

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

Tables and Figures

Table 1: Provision of 12-Month Continuous Eligibility

Twelve-month Continuous Eligibility	States
Yes	Alabama, California, Washington D.C., Idaho, Illinois, Iowa, Kansas, Louisiana, Mississippi, Maine, Michigan (after Jan 2003), New York, North Carolina, South Carolina, Wyoming (after Oct 2002), West Virginia (after Oct 2002).
No	Alaska, Colorado, Georgia, Hawaii, Kentucky, Missouri, Montana, Nevada, New Hampshire, North Dakota, Ohio, Oklahoma, Oregon, Rhode Island, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Wisconsin.
Complicated	Arizona, Arkansas, Connecticut, Delaware, Florida, Indiana, Maryland, Massachusetts, Minnesota, Nebraska, New Jersey, New Mexico, Pennsylvania, Washington.

Note: This table groups the states by whether or not they had provided 12 months of continuous eligibility during the sample period of 2000-2007. States in the first row had provided 12 months of continuous eligibility during the sample period; states in the second row had not, even though many of them allowed a 12-month renewal period with mandatory reporting of circumstance changes. The remaining states (the third row) either underwent changes in their provisions (CT, IN, MA, NE, NJ, NM, WA), the nature of which would greatly complicate the SIPP analysis (the three states that made a switch in row one are only included in the 2004 panel sample), or their continuous eligibility provisions differed across components of their public insurance programs (AR, AZ, FL, MD, MN, PA).

Source: NGA (2000-2008), Kaiser (2000-2011).

Table 2: Summary of Institutions for States Providing 12-Month Continuous Eligibility

State	Income Proof Requirement	Renewal Materials Sent (Months before expiration)	Presumptive Eligibility	CHIP Waiting Period	
				2001 Panel	2004 Panel
Alabama	Pay stubs w/in 1 month	1	N	Y	Y
California	A pay stub w/in 45 days	Vary by local office	Y	Y	Y
D.C.	Pay stubs w/in 1 month	3	N	N	N
Idaho	Pay stubs w/in 30 days	1.5	N	Y	Y
Illinois	Pay stubs w/in 30 days	2	Y	Y	N
Iowa	Pay stubs w/in 30 days	1.5	N	Y	N
Kansas	Pay stubs w/in 2 months	1.5	N	N	N
Louisiana	Pay stubs w/in 1 month	1	N	N	N
Maine	Pay stubs w/in 4 weeks	Vary by local office	N	Y	Y
Michigan	A pay stub w/in 30 days	Vary by local office	Y	Y	Y
Mississippi	Pay stubs w/in 1 month	0.5-2	N	N	N
New York	Pay stubs w/in 4 weeks	2-3	Y	N	N
North Carolina	Pay stubs w/in 1 month	1	N	Y	N
South Carolina	Pay stubs w/in 4 weeks	1	N	N	N
West Virginia	Pay stubs w/in 30 days	2	N	Y	Y
Wyoming	Pay stubs w/in 1 month	2	N	Y	Y

Note and source: This table summarizes the relevant institutional details.

1. Income proof requirement data are gathered from state application forms and instructions, except for Kansas and Michigan. These two states do not specify the recency requirement in their application forms, and phone calls are made to state agencies to collect more detailed information.

2. For the timing of the renewal process, information comes from government websites in California, D.C., Illinois, New York, North Carolina, South Carolina and West Virginia, as well as from phone calls to government agencies in the remaining states.

3. Presumptive eligibility data come from the NGA (2000-2008) and Kaiser (2000-2011); the set of states that provided presumptive eligibility during the 2001 panel did not change during the 2004 panel.

4. Waiting period data come from Kaiser (2000-2011); the letter "Y" indicates that a state had mandated a CHIP waiting period during the sample period for children whose private insurance was voluntarily dropped prior to program application.

Table 3: Public Insurance Spell, Child and Sample Unit Counts by Spell Types, Continuous Eligibility Status 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	7044	8183	5294	7076	2839	4060
12-Month Cont. Elig.	2582	2821	1934	2421	1057	1420
No 12-Month Cont. Elig.	2485	2927	1927	2559	1036	1453
Other States	1977	2435	1444	2112	755	1207

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

	Subsample Public Insurance Spells		No. of Kids with Public Insurance Spells		No. of SU with Kids on Public Insurance	
Sample	2001	2004	2001	2004	2001	2004
Full Sample	2582	2821	1934	2421	1057	1420
Long Gap Subsample	419	689	419	680	255	420
No Presumptive Eligibility nor CHIP Waiting Period	417	799	321	703	181	429
Excluding Kids Starting Pub. Insurance w/ Parent	2027	2484	1606	2164	896	1286
Two-parent Subsample	1242	1596	932	1391	492	780
Construction-retail Subsample	635	667	513	609	296	352
College-educated Parent Subsample	1837	2317	1411	2022	821	1210
Families with More than Two Children	1115	1212	838	1054	306	406

Note: The first three rows of Panel (a) show the number of public insurance spells, children and sample units by spell type. It then breaks down the fresh spell counts, excluding those for infants, children who moved across states during a spell or who were on SSI, by continuous eligibility provision status. Note that I do include children who moved across states as long as the move did not occur during a spell. As a result, the fourth row of Panel (a) is the sum of the last three rows in columns 1 and 2, but not in columns 3-6. Panel (b) gives the spell, child and sample unit counts in the full and subsamples. By construction, the first row of Panel (b) is the same as the fifth row of Panel (a).

Table 4: Variable Averages for Children in the Analysis Samples

Variable	2001 Panel (Spell Month 0)		2004 Panel (Spell Month 0)	
	Month 0	Month 1	Month 0	Month 1
Age	8.35	8.42	8.74	8.84
Female	0.49	0.49	0.49	0.49
Black	0.23	0.23	0.19	0.19
Family Size	4.2	4.2	4.1	4.1
Two-parent Family	0.51	0.51	0.58	0.58
Family Income (in 2010 $)	1888	1859	2399	2353
Fraction without Earnings	0.11	0.12	0.09	0.10
On Medicaid	0	1	0	1
On Food Stamps	0.17	0.21	0.17	0.21
On Welfare	0.04	0.06	0.04	0.05
Mom on Medicaid	0.18	0.35	0.21	0.32
Dad on Medicaid	0.07	0.15	0.09	0.15
Mom on Food Stamps	0.20	0.24	0.18	0.21
Dad on Food Stamps	0.09	0.11	0.08	0.11
Mom on Welfare	0.04	0.05	0.03	0.03
Dad on Welfare	0.01	0.01	0.00	0.01
Mom on UI	0.03	0.02	0.02	0.02
Dad on UI	0.04	0.04	0.02	0.02

Note: Variable averages 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. Medians are reported for the family income variable; means are reported for all other variables, for which the SIPP sampling weights are used.

Table 5: Model-Predicted Income Responses

		2001 Panel (in 2010 Dollars)		2004 Panel (in 2010 Dollars)	
ρ	e	Dip Magnitude	Rebound Magnitude	Dip Magnitude	Rebound Magnitude
4	0	176	176	371	371
1.47	0	211	211	468	468
0	0	243	243	563	563
4	0.15	263	181	479	391
1.47	0.15	272	233	571	529
0	0.15	285	285	685	685

Note: Dip-and-rebound magnitudes predicted by the model in the full analysis samples. The model is calibrated using SIPP panel income data, federal income tax rates and published CHIP eligibility threshold and spending data.

Table 6: Statistical Tests of Theoretical Predictions

(a) Comparing Empirical and Model-Predicted Rebound Magnitudes: 2001 Panel

Sample	Point Estimate	p-value: testing H_0: $y^{emp} = y^{\rho,e}$ vs. H_1: $y^{emp} < y^{\rho,e}$		
		$\rho = 4$, $e = 0$	$\rho = 1.47$, $e = 0$	$\rho = 0$, $e = 0$
Full Sample	-147	0.03^{**}	0.02^{**}	0.01^{**}
Subsample 1	-1079	$< 0.01^{***}$	$< 0.01^{***}$	$< 0.01^{***}$
Subsample 2	-225	$< 0.01^{***}$	$< 0.01^{***}$	$< 0.01^{***}$
Subsample 3	-124	0.06^{*}	0.05^{**}	0.04^{**}
Subsample 4	-374	0.02^{**}	0.01^{**}	$< 0.01^{***}$
Subsample 5	-619	$< 0.01^{***}$	$< 0.01^{***}$	$< 0.01^{***}$
Subsample 6	-136	0.07^{*}	0.05^{**}	0.04^{**}
Subsample 7	-193	0.03^{**}	0.02^{**}	0.02^{**}

(b) Comparing Empirical and Model-Predicted Rebound Magnitudes: 2004 Panel

Sample	Point Estimate	p-value: testing H_0: $y^{emp} = y^{\rho,e}$ vs. H_1: $y^{emp} < y^{\rho,e}$		
		$\rho = 4$, $e = 0$	$\rho = 1.47$, $e = 0$	$\rho = 0$, $e = 0$
Full Sample	-564	$< 0.01^{***}$	$< 0.01^{***}$	$< 0.01^{***}$
Subsample 1	-1409	$< 0.01^{***}$	$< 0.01^{***}$	$< 0.01^{***}$
Subsample 2	-709	$< 0.01^{***}$	$< 0.01^{***}$	$< 0.01^{***}$
Subsample 3	-720	$< 0.01^{***}$	$< 0.01^{***}$	$< 0.01^{***}$
Subsample 4	-940	$< 0.01^{***}$	$< 0.01^{***}$	$< 0.01^{***}$
Subsample 5	-735	$< 0.01^{***}$	$< 0.01^{***}$	$< 0.01^{***}$
Subsample 6	-594	$< 0.01^{***}$	$< 0.01^{***}$	$< 0.01^{***}$
Subsample 7	-678	$< 0.01^{***}$	$< 0.01^{***}$	$< 0.01^{***}$

Note: Presented are point estimates of the seam-bias adjusted empirical rebound magnitude, y^{emp}, along with p-values from testing the labor supply model in various samples and under different parameter values. Subsample 1 is the long gap sample; subsample 2 excludes states providing presumptive eligibility or mandating a CHIP waiting period; subsample 3 excludes children whose parents took up Medicaid when they began their public insurance spell; subsample 4 consists of children in two-parent families; subsample 5 is the construction-retail sample; subsample 6 consists of children in families with a college-educated parent; subsample 7 consists of children with more than one sibling. The p-values come from an asymptotic normal approximation with bootstrapped s.e.'s; the number of repetitions is based on Andrews and Buchinsky (2000).
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7: Comparisons with Counterfactual Groups

Counterfactual Group	Estimand	2001 Panel		2004 Panel	
		Point Estimate	p-value	Point Estimate	p-value
Low-income Group	SDD_4	699	0.19	−217	0.77
No-continuous-eligibility States	Δy^{emp}	287	0.08^{*}	−649	0.99

Note: The point estimates are in 2010 dollars. The symmetric difference-in-differences estimand SDD_4 defined in section 6.2 and D comes from the comparison of income processes between high and low income groups. The p-values in the first row are from the one-sided hypothesis test: $H_0 : SDD_4 = 0$ vs. $H_1 : SDD_4 > 0$. Δy^{emp} gauges the difference in income rebound magnitudes between states providing 12-month continuous eligibility and those that did not. The p-value in the second row comes from the one-sided hypothesis test: $H_0 : \Delta y^{emp} = 0$ vs. $H_1 : \Delta y^{emp} > 0$. The hypothesis tests are conducted via bootstrap with the number of repetitions based on Andrews and Buchinsky (2000).

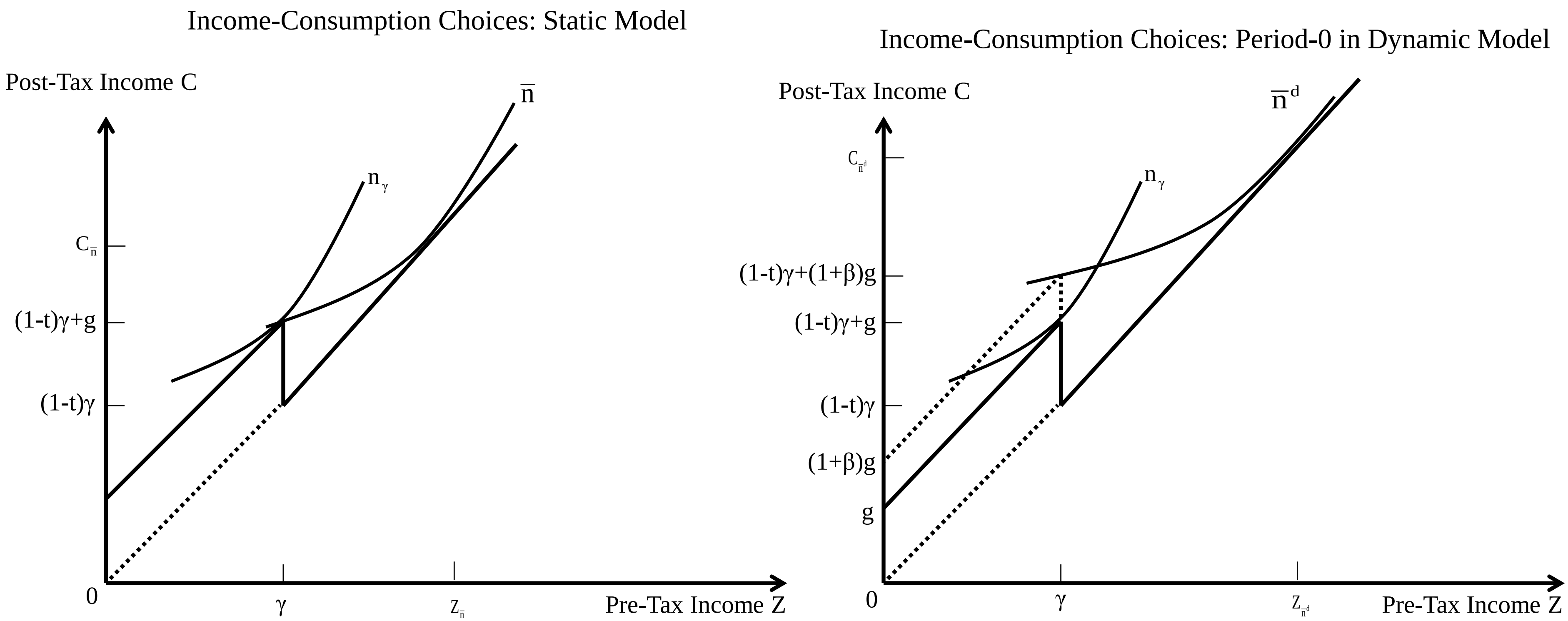
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 8: Optimal Length of the Continuous Eligibility Period from Welfare Calculations

Recertification Cost		Optimal Length of the Continuous Eligibility Period (τ)	
ϕ	κ	2001 Panel	2004 Panel
\$0	\$0	1	1
\$0	\$19	4	4
\$0	\$38	4	4
\$19	\$0	8	8
\$19	\$19	8	12
\$19	\$38	12	12
\$38	\$0	12	12
\$38	\$19	12	12
\$38	\$38	12	16

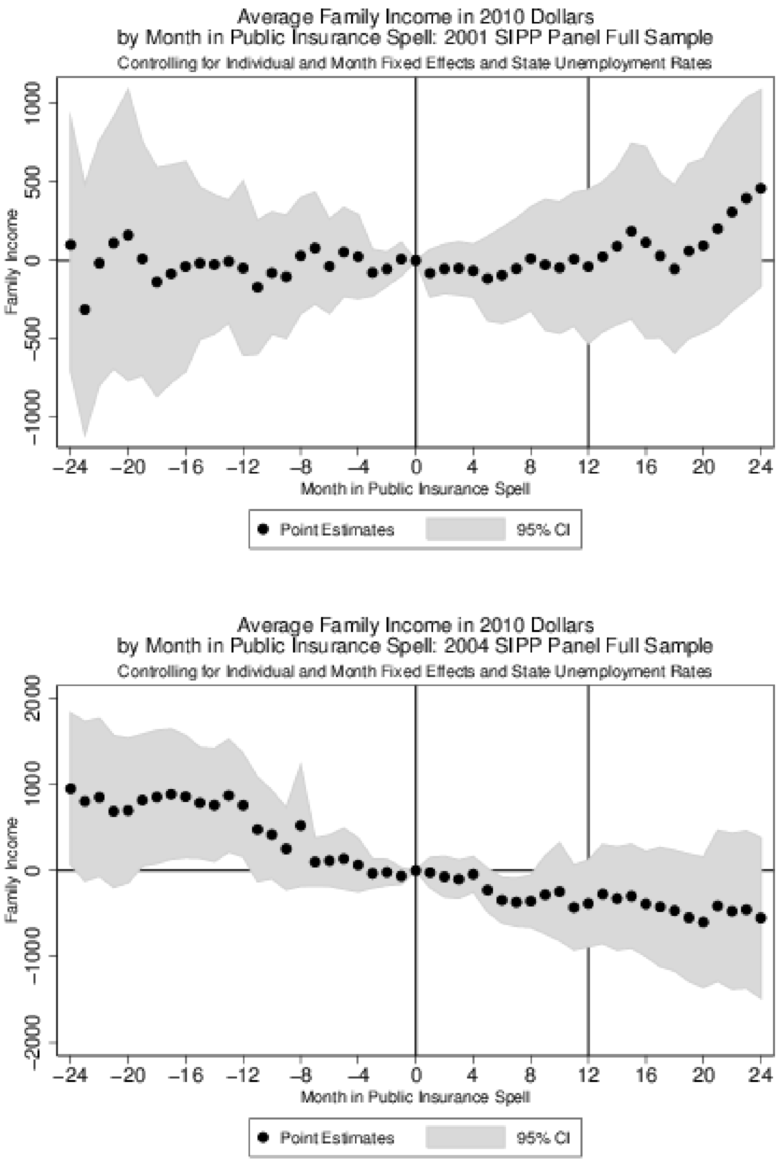
Note: The optimal lengths of the continuous eligibility period, τ, are calculated based on the framework in section 7. The choice set of τ is $\{1, 2, ..., 35\}$, and the social welfare function parameter $\eta = 1$. The calculation is carried out for different recertification costs ϕ and κ (in 2010 dollars). The SIPP sample that serves the basis of the calculation consists of families with children who had appeared every month during the 2001 and 2004 panels.

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



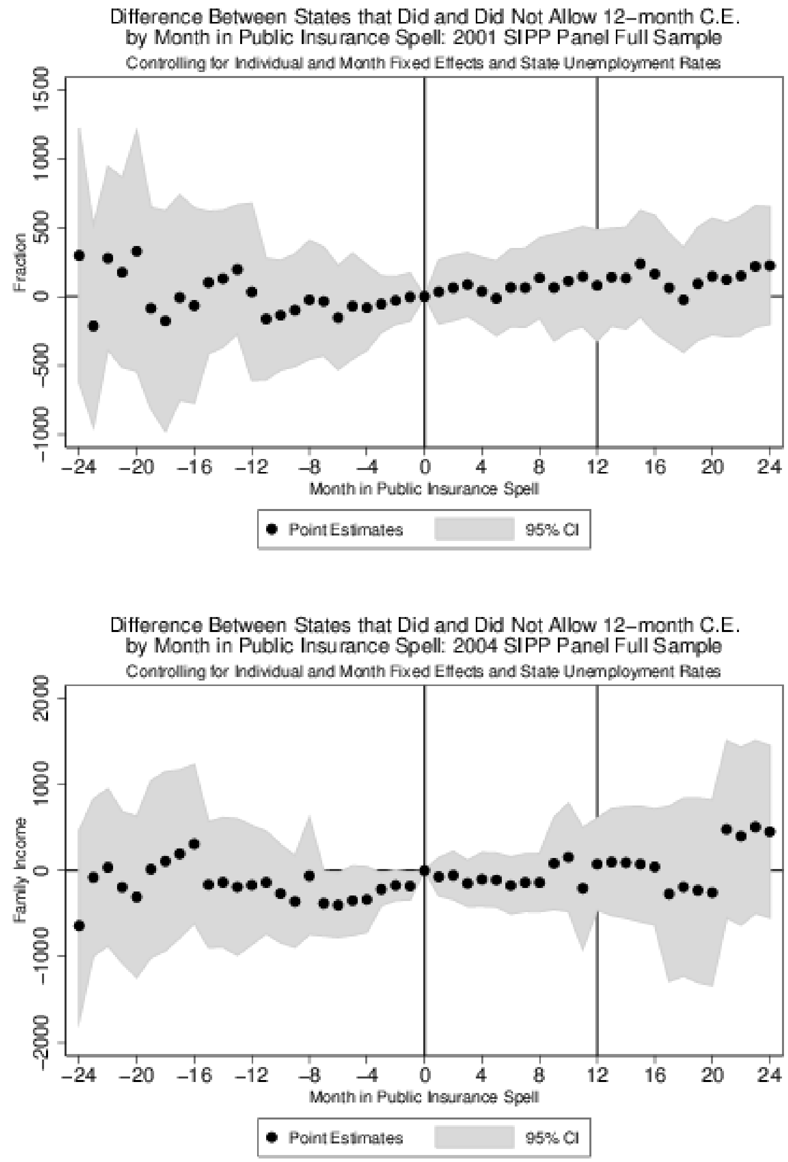
Note: The left and right panels illustrate agents' income-consumption choices in the static (subsection 3.1) and dynamic model (subsection 3.2), respectively. The static model assumes that income eligibility is checked every period, whereas in the dynamic model it is checked every two periods. In the left panel, I plot the static budget constraint (2) and the indifference curves of two distinct agents – one of type n_γ and one of $\bar{n}$. As stated in the text, an n_γ-agent chooses income γ absent the program, an $\bar{n}$-agent is indifferent between program participation and non-participation, and agents whose type is in the interval $[n_\gamma, \bar{n}]$ choose pre-tax income $Z = \gamma$ and participate in the program. In the right panel, the indifference curve of the $\bar{n}^d$-agent is drawn along with that of n_γ, and the budget constraint (2) is also present for comparison purposes. In the corresponding two-period dynamic model, agents whose type is in the interval $[n_\gamma, \bar{n}^d]$ choose pre-tax income γ in period 0. An $\bar{n}^d$-agent is indifferent between participating and not participating in a constantly-monitored program with benefit $(1+\beta)g$. The figure reveals that when the utility function is quasi-linear, doubling the length of the recertification period induces the same agents to participate in the program as increasing the program benefit level from g to $(1+\beta)g$.

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



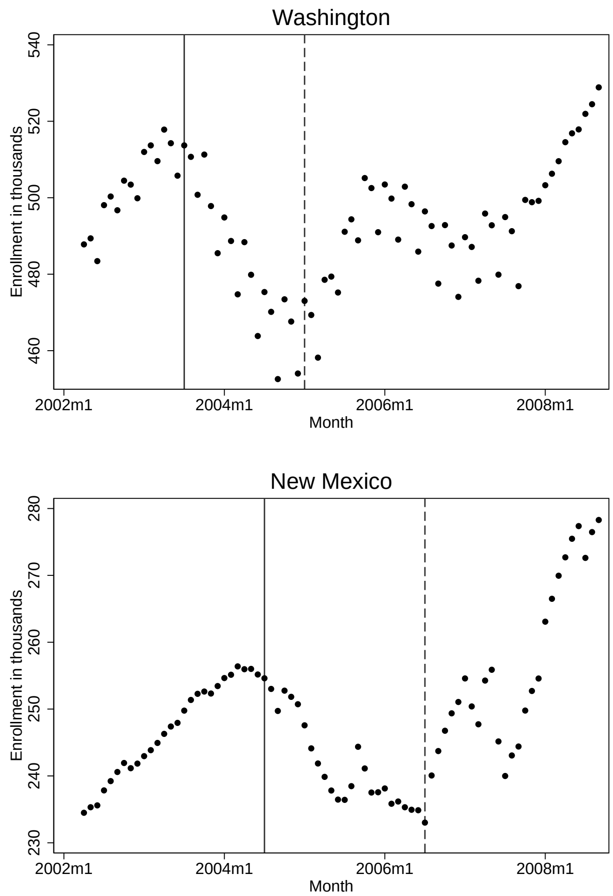
Note: Plotted are the estimated coefficients and pointwise 95% confidence intervals from fixed effect regressions of monthly family income in 2010 dollars on a set of spell month indicators. Month 0 (the month right before the start of a fresh Medicaid/CHIP spell) is the omitted category, and the corresponding coefficient is 0 by construction.

Figure 3: Difference in Average Income between States with and without 12-month Continuous Eligibility



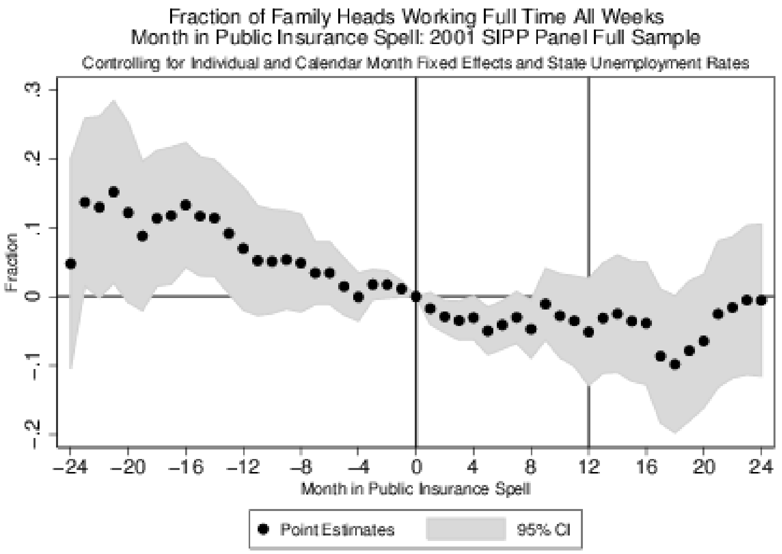
Note: Plotted are the point estimates and pointwise 95% confidence intervals of the differences in the income processes between children residing in states providing 12-month continuous eligibility and those who did not. Month 0 (the month right before the start of a fresh Medicaid/CHIP spell) is the omitted category, and the corresponding coefficient is 0 by construction.

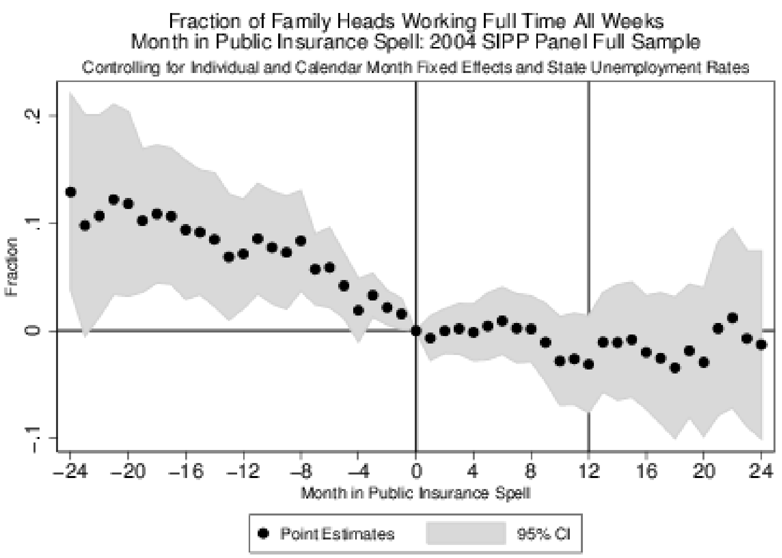
Figure A.1: Number of Medicaid Enrollees around Changes in the Eligibility Recertification Frequency



Note: The solid vertical line indicates the month when the eligibility recertification interval decreased from 12 months to 6 months, and the dashed vertical line indicates the month when the interval increased from 6 months to 12 months.

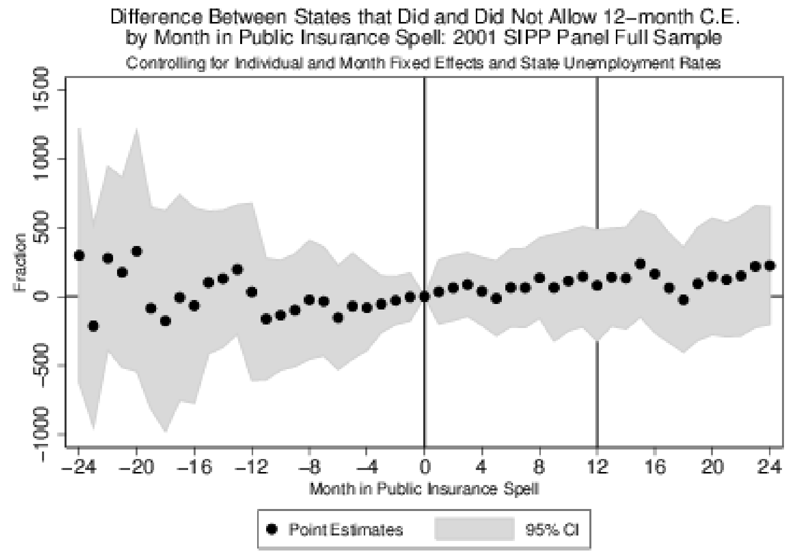
Figure A.2: Fraction of Family Head Working Full Time in Medicaid Spell: Full Sample

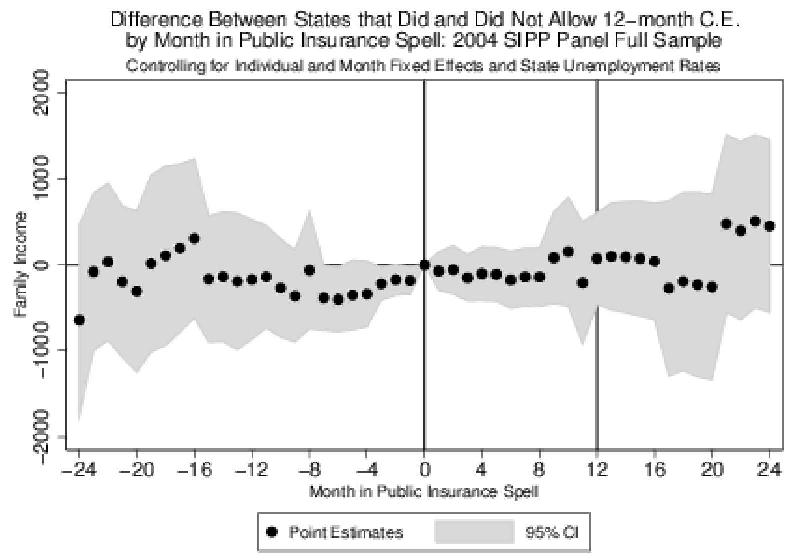




Note: Plotted are the estimated coefficients and pointwise 95% confidence intervals from fixed effect regressions of whether the family head had worked full time on a set of spell month indicators. Month 0 (the month right before the start of a fresh Medicaid/CHIP spell) is the omitted category, and the corresponding coefficient is 0 by construction.

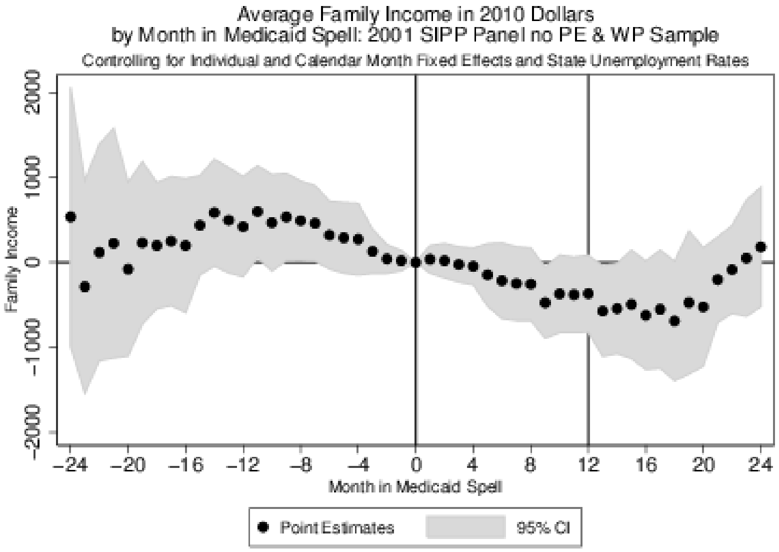
Figure A.3: Average Family Income by Month in Medicaid Spell: Long Gap Sample





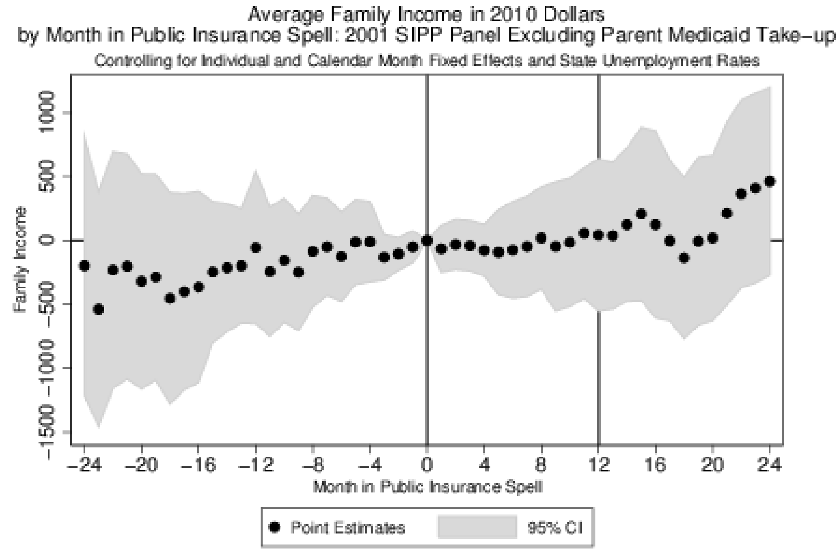
Note: Plotted are the estimated coefficients and pointwise 95% confidence intervals from fixed effect regressions of monthly family income in 2010 dollars on a set of spell month indicators. Month 0 (the month right before the start of a fresh Medicaid/CHIP spell) is the omitted category, and the corresponding coefficient is 0 by construction. This subsample only includes children who were not covered by public insurance for 12 months before the start of a spell.

Figure A.4: Average Family Income by Month in Medicaid Spell: Subsample with No-Presumptive-Eligibility and No-Waiting-Period States



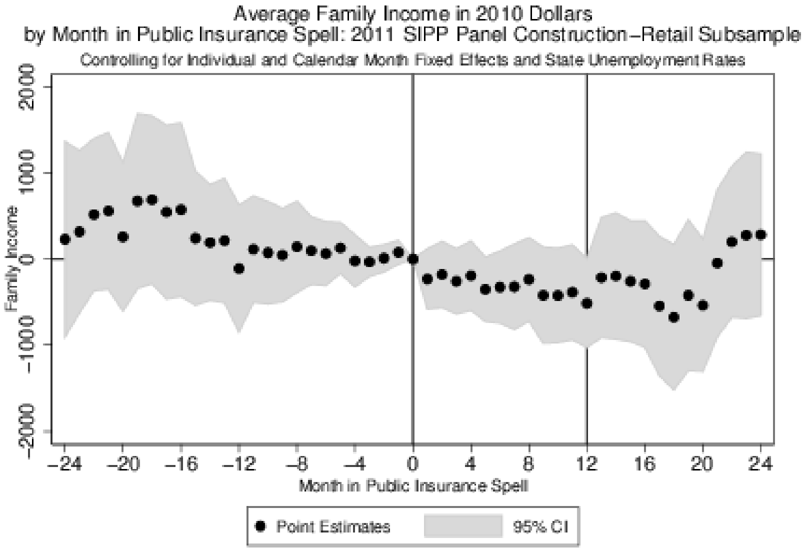
Note: Plotted are the estimated coefficients and pointwise 95% confidence intervals from fixed effect regressions of monthly family income in 2010 dollars on a set of spell month indicators. Month 0 (the month right before the start of a fresh Medicaid/CHIP spell) is the omitted category, and the corresponding coefficient is 0 by construction. This subsample is restricted to children in states that provided no presumptive eligibility nor mandated a CHIP waiting period.

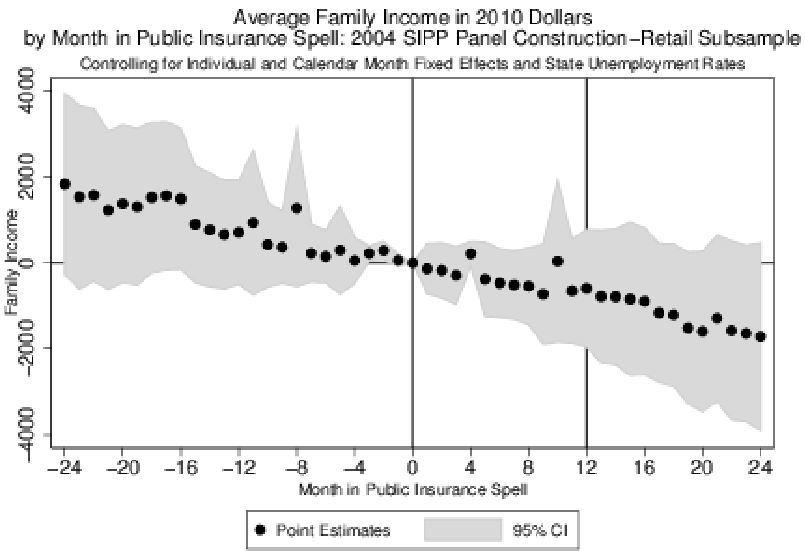
Figure A.5: Average Family Income by Month in Medicaid Spell: Subsample Excluding Children Beginning Public Insurance with Parent



Note: Plotted are the estimated coefficients and pointwise 95% confidence intervals from fixed effect regressions of monthly family income in 2010 dollars on a set of spell month indicators. 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. This subsample excludes children whose parents took up Medicaid when they began their public insurance spell.

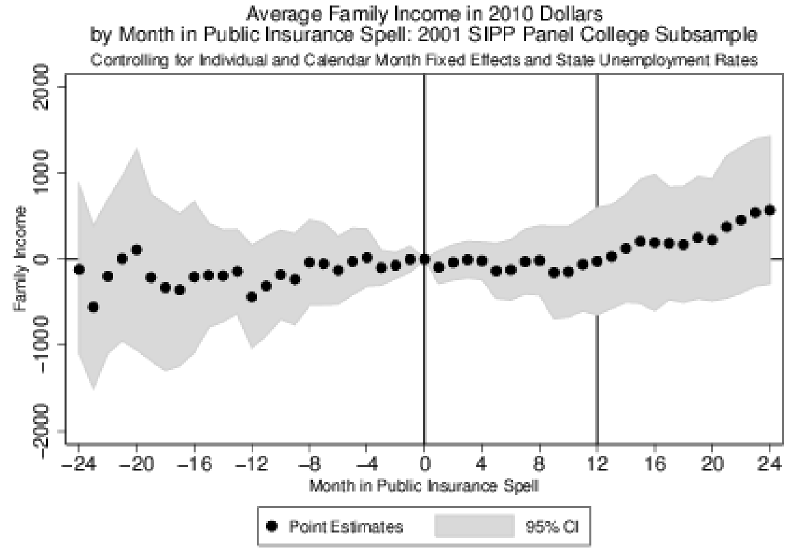
Figure A.6: Average Family Income by Month in Medicaid Spell: Subsample with Two-parent Families

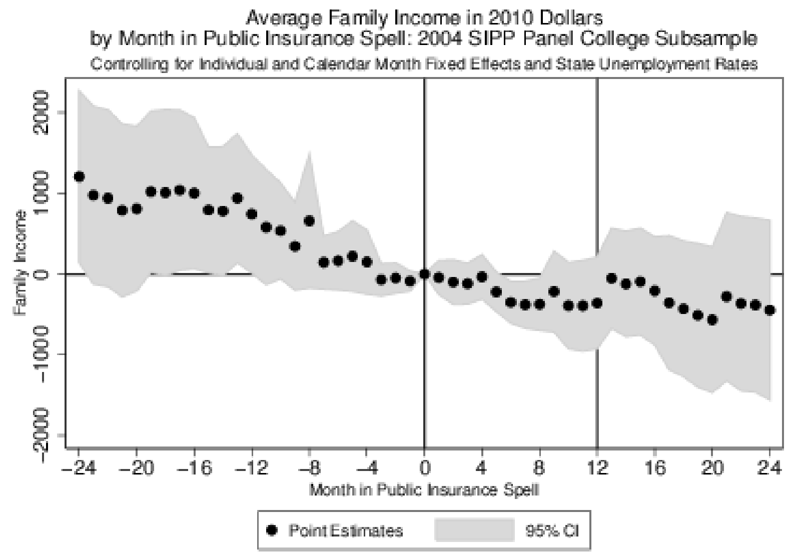




Note: Plotted are the estimated coefficients and pointwise 95% confidence intervals from fixed effect regressions of monthly family income in 2010 dollars on a set of spell month indicators. Month 0 (the month right before the start of a fresh Medicaid/CHIP spell) is the omitted category, and the corresponding coefficient is 0 by construction. This subsample consists of children living in two-parent families.

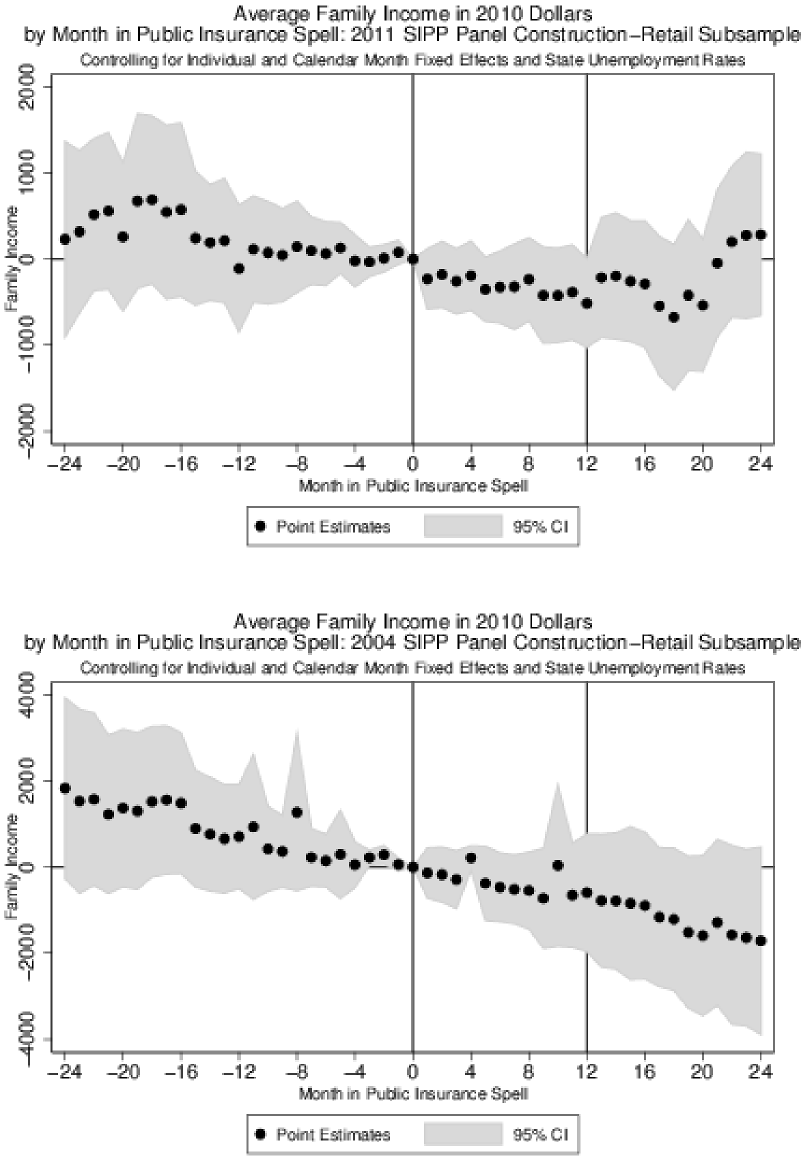
Figure A.7: Average Family Income by Month in Medicaid Spell: Subsample with Parents in Construction or Retail Industries





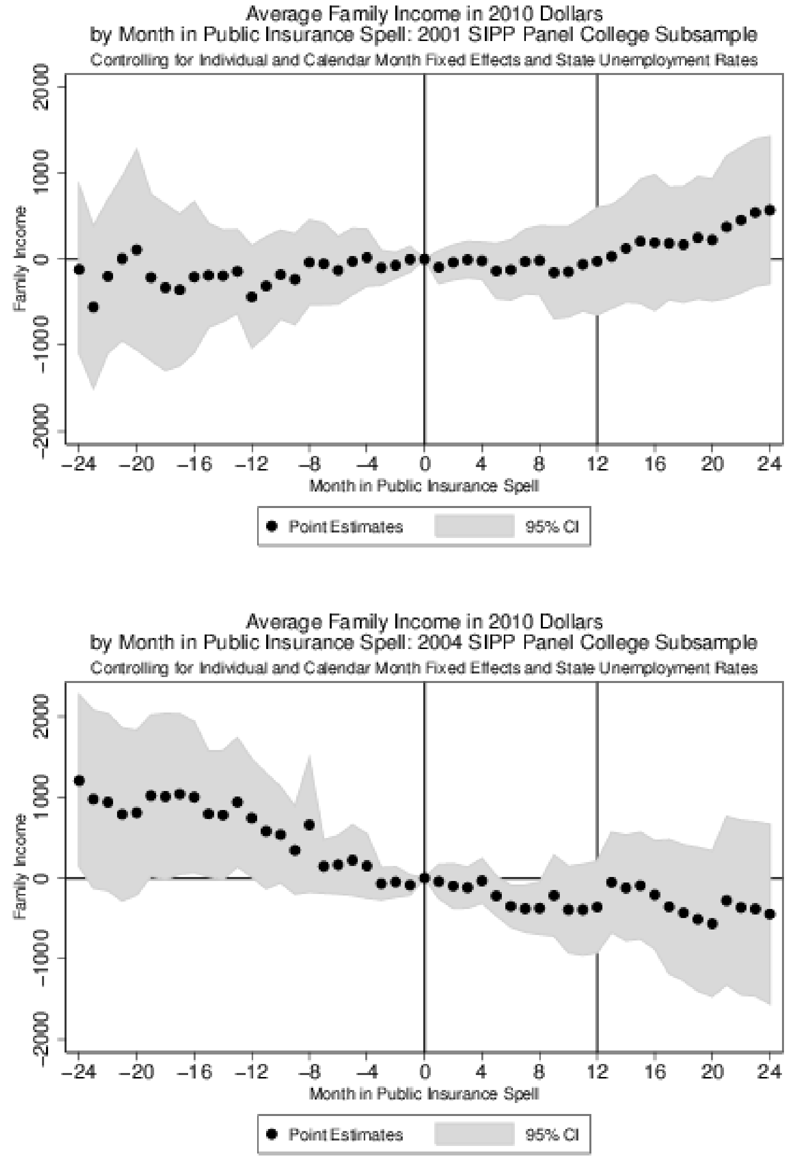
Note: Plotted are the estimated coefficients and pointwise 95% confidence intervals from fixed effect regressions of monthly family income in 2010 dollars on a set of spell month indicators. Month 0 (the month right before the start of a fresh Medicaid/CHIP spell) is the omitted category, and the corresponding coefficient is 0 by construction. This subsample consists of children whose parents had worked in the construction or retail industries.

Figure A.8: Average Family Income by Month in Medicaid Spell: Subsample with College-educated Parent



Note: Plotted are the estimated coefficients and pointwise 95% confidence intervals from fixed effect regressions of monthly family income in 2010 dollars on a set of spell month indicators. 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. This subsample consists of children with a college-educated parent.

Figure A.9: Average Family Income by Month in Medicaid Spell: Subsample of Families with More than Two Children



Note: Plotted are the estimated coefficients and pointwise 95% confidence intervals from fixed effect regressions of monthly family income in 2010 dollars on a set of spell month indicators. 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. This subsample consists of children with more than one sibling.