Income Manipulation to Subsidized Health Insurance Programs: Evidence from Massachusetts*

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Abstract

This paper analyzes the income manipulation to cutoffs in eligibility for a subsidized program in the Massachusetts health insurance reform, the state-level precursor to federal health care reform. Using data from the American Community Survey, I test for the existence of income manipulation and find clear evidence around the cutoffs of 150 percent and 300 percent of Federal Poverty Level. The lower cutoff falls between plans with zero and non-zero out-of-pocket premiums, and the effect is concentrated among the self-employed. The higher cutoff falls between plans with the largest difference of out-of-pocket premiums, and is concentrated among wage workers. Based on the evidence of manipulation, I estimate the elasticity of labor supply with respect to wage rate, and calculate the welfare loss due to the subsidized program.

Keywords: Massachusetts Health Reform, Health insurance subsidy, Income manipulation, Labor supply response

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1 Introduction

In the U.S. health care reform created by the Affordable Care Act (ACA), eligible low- and middle-income households will receive tax credits as subsidies to purchase health insurance plans. The subsidy schedules regulate income cutoffs on the eligibility of these programs, and generate non-linear budget constraints on the consumption of the participated population. While the programs will have direct impact on expanding insurance coverage, it may create incentives of behavioral response. For example, enrollees with relatively greater income will have incentives to lower their income in order to receive higher subsidies. Previous literature has provided evidence of behavioral response to programs such as Medicaid (Moffit & Wolf (1992), Yelowitz (1995)), Income Tax (Saez (2010)), and Social Security (Friedberg (2000)).

The population response has economic importance. The income manipulation may distort labor markets, since labor income is a main source of income for the majority of the population, and controlling labor supply is a main channel of varying income. This change will cause deviation of the labor supply from the optimal level, and will create inefficiency in the labor markets. The response also has policy significance in projecting the number of eligible enrollees for the welfare programs. In the Massachusetts health reform, which was enacted in 2006 and served as a template of the national reform, the authority (Health Connector (2010)) reported that the legislative conferees estimated the spending for a subsidized program, which I focus on in this study, would be $725 million in fiscal year 2009. However, the real spending turned out to be $805 million. The report claimed that the difference came from an unexpected increase of eligible enrollees for the program.

In this paper, I analyze the behavioral response of income manipulation to the subsidized insurance program in the Massachusetts health reform. The subsidy has a piecewise structure, and income cutoffs sort eligible participants into different income tiers. Households falling in higher tiers receive smaller subsidies and pay more out-of-pocket premiums. Hence those with income slightly above the cutoffs have large incentives to lower their income in order to be eligible for greater subsidies.

In this analysis, income manipulation is tested with the Regression Discontinuity (RD) approach developed by McCrary (2008). The approach is based on the assumption that the density of the income distribution would be continuous at the cutoff when there is no program intervention, and the density is likely to be discontinuous when households have manipulated their income. McCrary (2008) constructs a statistic testing the existence of discontinuity at the cutoff. I construct a difference-in-difference measure by taking the difference of the statistics in McCrary (2008) between the pre-reform and post-reform periods, due to the concern that other social programs could also generate discontinuity on income distribution. This measure captures the pre-post change of income above and below the cutoff, and is not affected by other programs implemented before the reform.

Using data from the American Community Survey (ACS), I estimate the discontinuity measure at the cutoffs regulated by the subsidized program as well as other levels of income. I find clear evidence of income manipulation: income discontinuity exists around and only around the cutoffs generated by the subsidy schedule. Among the four cutoffs created by the subsidy schedule, the results show discontinuity around two cutoffs: 150 percent of Federal Poverty Level (FPL), and 300 percent of the FPL. The former is the cutoff between plans with zero and non-zero out-of-pocket premiums, and the latter is between plans with the largest subsidy difference. The results suggest the conclusion that the subsidized program causes income manipulation of the population. The results also indicate that the population responds actively when they face choices between free and non-free plans, and when the incentive is large enough.

By exploring the effects in subgroups, I find the manipulation around the cutoff of 150 percent is concentrated among the self-employed, the group who may plausibly be able to manipulate their income more easily. The result is similar to the finding in Saez (2010) who finds bunching of earnings at the first kink point of the Earned Income Tax Credit, which is concentrated among the self-employed. The income manipulation around the cutoff of 300 percent of FPL is concentrated among wage-workers.

I then assume that all the income change comes from the change of labor supply, and estimate the labor supply elasticity with respect to the wage rate, based on the method introduced by Saez (2010). The identification of the elasticity comes from the change of income distribution for households with income around the cutoffs between the pre-reform and post-reform periods. Households with income slightly above the cutoff will reduce their income to the levels below the cutoff. Therefore the income density in the post-reform period is higher in the ranges below the cutoff, and is lower in the ranges above the cutoff, comparing to the density in the pre-reform period.

I incorporate income uncertainty in my model, and estimate the income variation together with the labor supply elasticity, based on household characteristics and the subsidy regulation. Different estimations are conducted using the whole samples, the wage workers, and the self-employed. The results on labor supply elasticity are all around 0.01. Although the elasticity is very small, it does not mean that people do not have incentive to manipulate their income. The population with income slightly above the cutoff have incentives to manipulate income even if the elasticity is zero. The elasticity determines whether the population with relatively high income, who face the tradeoff between leisure and income, are willing to lower their income or not. The standard deviation of income is around 0.1% in terms of FPL in all estimations. The result indicates that the income uncertainty the population face is very samll. For example, for a single person with income about $10,000, the standard deviation of income is about $10.

I also estimate the welfare impact of the behavioral response due to the subsidized program. Based on the estimation results, I calculate the average income decrease for the population who have incentive to control their income. I also estimate the number of population who actually changed their income by comparing samples between Massachusetts and Connecticut, a control state who has similar demographics as Massachusetts. The welfare loss, which is measured as the total decreased income, is estimated as $2.8 million in 2008.

Recent studies have shown the impacts of health care reform on young adults (Antwi et

al. (2013) and Long et al. (2010)), children (Miller (2012)), insurance premiums (Graves & Gruber (2012)), low income families (Chan & Gruber (2010)), and other aspects (Ericson and Starc (2012), Chandra et al. (2010), Hackmann et al. (2012), Kolstad and Kowalski (2012a, 2012b)). My work provides the first evidence on the behavioral response to the subsidized program for low- and middle-income households in the Massachusetts reform, and the results are of special interest in projecting the population response to the national reform.

A large literature has focused on the incentive effects to U.S. welfare system (see Moffit (1992) for a literature review). Previous studies have found negative effects of welfare program on labor supply. In Medicaid, for example, Winkler (1991) finds disincentive on female head labor supply. Moffitt & Wolfe (1992) find negative employment rate in program benefit. Pei (2012) examines labor supply response of parents whose children are eligible for CHIP. My study provides new evidence of the negative labor supply effects on a newly initiated welfare program.

My work also contributes to the growing literature using nonlinear budget constraint to identify labor supply elasticity. Brown (2013) estimates the life time labor supply using the reform of the California teachers' pension system. Friedberg (2000) estimates the labor supply elasticity based on the social security earnings test. My work is closely related to these studies in estimating the elasticity by using a subsidized program in the health reform. My analysis is based on the model developed by Saez (2010) who using the bunching evidence in taxes schedule to estimate labor supply. I extend his model by allowing the population be aware of income uncertainty. This feature has the advantage of predicting the targeted income to distribute below the cutoff, but not exactly at the cutoff. My model provides a general framework to estimate labor supply elasticity, and can be applied to other programs which create non-linear budget constraints.

The paper is organized as follows. Section 2 introduces the policy of the program in Massachusetts reform. Section 3 presents the graphical evidence of the income manipulation. Section 4 shows the structural model and estimation results. Section 5 assesses the welfare

impact. Section 6 concludes.

2 Subsidized Health Insurance Program in the Massachusetts Health Reform

In the Massachusetts reform, people are required to purchase insurance plans, or they have to pay penalties. In 2007, the penalty was $219, and in later years the penalty was up to 50 percent of the premium for the lowest cost plan available through the Health Connector, which is the marketplace for insurance plans in Massachusetts.[1] Three programs are provided to the non-elderly population who are not covered by the Employer Sponsored Health Insurance: MassHealth, Commwealth Care (CommCare), and Commonwealth Choice (CommChoice). MassHealth is the Medicaid program that provides free health insurance to low-income individuals. CommCare is a government-subsidized program targeted to the population with low and middle income. Only individuals with household income below 300 percent FPL are eligible for the program. CommChoice is an unsubsidized program. People who are not eligible for either MassHealth or CommCare can purchase plans in CommChoice by paying the full premiums. This paper focuses on the CommCare program, which involves 165,000 enrollees and $805 million government spending in 2009.

The CommCare program has a piecewise subsidy schedule, where four income cutoffs (150 percent of the FPL, 200 percent FPL, 250 percent FPL, and 300 percent FPL) sort participants into four income tiers: 0-150 percent FPL, 150-200 percent FPL, 200-250 percent FPL, and 250-300 percent FPL.[2] Health plans are provided by competing insurance firms. Within each tier one firm only provides one plan, and the same firm can provide different

[1] The information on the regulation in the health reform comes from reports published by the Division of Health Care Finance and Policy (2008-2010), and the Massachusetts Health Connector and the Department of Revenue (2007-2009).

[2] In 2008, the FPL for a family with a single person was $10,400, and the amount increases by $3,600 with an additional person included in the family.

plans across tiers. Plans vary at several dimensions, such as benefit design, provider network, and premiums.

The out-of-pocket premium and cost-sharing are the two characteristics that differ for enrollees in different income tiers. I take the plans with the lowest premiums in each tier for example, and show details in Figure 1. In October 2008, the total premium is $396 per month for plan in all tiers, and the out-of-pocket premiums are $0, $39, $77, and $116 per month if their household income are within 0-150 percent FPL, 150-200 percent FPL, 200-250 percent FPL, and 250-300 percent FPL, respectively.[3] The information on out-of-pocket premiums is shown in the first row of Figure 1.

If household income are greater than 300 percent of FPL, people are only eligible for plans in the unsubsidized market, CommChoice, or pay penalties. In CommChoice three types of plans are provided with different generosities: Bronze, Silver, and Gold plans. The generosity of the plan for the 250-300 percent FPL in CommCare is between the level of generosity of Bronze and Silver plans in CommChoice, so individuals need to pay about $238 per month in the non-subsidized program, which is the mean of premiums for the lowest cost Bronze plan and lowest cost Silver plan, in order to obtain a comparable plan in the subsidized program.

For cost-sharing, plans vary at several dimensions, such as copayment, coinsurance rate, and out-of-pocket maximum. In general, the plans in lower income tiers are more generous than those in higher income tiers. For example, in 2011, the plan for 100-150 percent FPL has no copayment, no coinsurance, and a $200 maximum out-of-pocket payment for drugs, while the plan for 200-250 percent FPL has a copayment range from $15 to $250, according to different services, 10 percent coinsurance for medical equipment, and an $800 maximum out-of-pocket payment for drugs. For a typical enrollee, the cost-sharing is estimated as $0, $78, $265, and $265 per year if their household income are within 0-150 percent FPL, 150-200 percent FPL, 200-250 percent FPL, and 250 percent-300 percent FPL, respectively. The amounts of cost-sharing in different income tiers are shown in the second row in Figure

[3]Premiums are the lowest priced plans available for a 35-year-old individual living in Boston. Data are rounded to the nearest whole dollar.

1. More details on the estimation of cost-sharing are shown in Appendix A1.

Therefore, the total expected out-of-pocket costs (premium plus cost-sharing) for enrollees are \$0, \$546, \$1,189, and \$1,657 among the four tiers, and the cost for unsubsidized plans are \$3,121, which are displayed in the third row of Figure 1. The difference is \$546, \$643, \$468, and \$1,464 at the cutoff of 150 percent FPL, 200 percent FPL, 250 percent FPL, and 300 percent FPL, respectively, which is shown in the fourth row in Figure 1. The cost differences provide large incentives for people with household income around those cutoffs to lower their income. For example, the 150 percent FPL was \$21,000 for a family of two in 2008. If both family members need to purchase plans from the CommCare program, the cost difference can be as high as \$1,092 per year.

3 Regression Discontinuity on Income Distribution

3.1 Methodology

I use Regression Discontinuity (RD) methodology to test the existence of income manipulation. This approach was developed by McCrary (2008) and is based on the assumption that the density of the income would be continuous at the cutoffs without program intervention, and the density is likely to be discontinuous when people are able to manipulate their income.

As McCrary (2008) states, the estimation proceeds in two steps. In the first step, a finely gridded histogram is obtained. In the second step, the histogram is smoothed by using local linear regression separately on either side of the cutoff. McCrary (2008) proposes a formal test on the hypothesis that the discontinuity of the "running variable" at the cutoff is zero. The test is based on an estimator for the discontinuity, θ, which is defined as the log difference between the left limit and the right limit of the density at the cutoff of the running variable.

Specifically, the form is

$$\theta = \ln \lim_{I \downarrow c} f(I) - \ln \lim_{I \uparrow c} f(I) \equiv \ln f^{+} - \ln f^{-},$$

where I is the running variable (in my case, income), $f(\cdot)$ is the density function, and c is the cutoff.

The benefit of the RD approach is that it allows for point esitmation and inference. The parameter $\hat{\theta}$ is estimated as

$$\begin{aligned} \hat{\theta} \equiv & \quad \ln \hat{f}^{+} - \ln \hat{f}^{-} \\ = & \quad \ln\{\sum_{x_j > c} K(\tfrac{X_j - c}{h}) \tfrac{S^{+}_{n,2} - S^{+}_{n,1}(x_j - c)}{S^{+}_{n,2} S^{+}_{n,0} - (S^{+}_{n,1})^2} Y_j\} \\ & - \ln\{\sum_{x_j < c} K(\tfrac{X_j - c}{h}) \tfrac{S^{+}_{n,2} - S^{+}_{n,1}(x_j - c)}{S^{+}_{n,2} S^{+}_{n,0} - (S^{+}_{n,1})^2} Y_j\}, \end{aligned}$$

where $S^{+}_{n,k} = \sum_{X_j > c} K((X_j - c)/h)(X_j - c)^k$ and $S^{-}_{n,k} = \sum_{X_j < c} K((X_j - c)/h)(X_j - c)^k$.

McCrary (2008) proves that the $\hat{\theta}$ has the following normal distribution if certain conditions are satisfied:

$$\sqrt{nh}(\hat{\theta} - \theta) \xrightarrow{d} N(B, \frac{5}{24}(\frac{1}{f^{+}} + \frac{1}{f^{-}}))$$

where $B = \frac{H}{20}(\frac{-f^{+''}}{f^{+}} - \frac{-f^{-''}}{f^{-}})$, n is the number of observations, h is bandwith, and $h^2\sqrt{nh} \longrightarrow H \in [0, \infty)$.

3.2 Data

This paper uses data from the American Community Survey (ACS), which is part of the Decennial Census Program by the U.S. Census Bureau.[4] The survey includes monthly rolling samples of households, and the nationally-representative data have been available each year since 2000. I use the samples from 2005 and 2008 that include observations in both pre-reform and post-reform periods. The survey selected 1-in-100 sample households from the population; the sample size is around 27,000 households (65,000 individuals) each year. I exclude individuals under the age of 19, who would be eligible for Medicaid if their household income is below 300 percent FPL, and individuals older than 64, who would be eligible for Medicare. I also exclude individuals with very high income (above 1,500 percent FPL) who would not be affected by the subsidized program. Samples from Connecticut and other years are also included for the robustness check.

Table 1 shows the descriptive statistics for the population in Massachusetts in 2005 and 2008 separately. The number of observations is 36,358 in 2005 and 36,231 in 2008. Mean age is about 42 in both years. The mean of household income is $78,134 in 2005, and $86,387 in 2008. There are about 27% of the population with household income below 300 percent FPL. the percentage of the population that falls in the income ranges of the subsidized program. The table also shows the statistics on sub-group populations by working status (wage worker, self-employed, and unemployed) and age (young being 19-35 and old being 36-64). The majority of the population are wage workers, and about one third of the samples are young adults.

Figure 2 shows the histograms of income distribution for households within income range 0-500 percent FPL in 2005, the pre-reform period, and in 2008, the post-reform period. The blue columns show the frequency of people with income just below each cutoff. The graphs

[4]To my knowledge, ACS is the only available data that is large enough to support this analysis, since it focuses on income distribution. The ideal data is the income tax data from the IRS, which has both a large enough sample size and less measurement error than the ACS data. However, the full sample income tax data was not available during the time I was finishing the project. The analysis can be replicated using the tax data when it is available in the future.

show weak evidence on income shift from the right to the left of the cutoffs.

3.3 Graphical Evidence

This section shows the estimation results based on the RD methodology. Figure 3A reports the RD estimation at the first income cutoff of 150 percent FPL in Massachusetts in 2008. The x-axis is the level of income as percent of FPL, and the y-axis is the income density. Dots represent the density at each income level from 0 percent to 1,500 percent of FPL. The curves are the local linear regression estimates using a triangle kernel based on the income density. The optimal binsize and bandwidth are selected automatically by the program provided by McCrary (2008). The 95 percent of confidence interval is also shown in each graph.

Figure 3A illustrates the estimation in 2008 when the program was implemented, and the results show significant discontinuity at the cutoff. The left limit of the density is higher than the right limit at the cutoff. However, it is possible that the discontinuity at the cutoff had existed before the reform, therefore I test the hypothesis in 2005 when the program was not implemented. The curve in Figure 3B is smooth and shows no discontinuity at the cutoff. Combining results in both years, the graphical evidence suggests that the existence of income manipulation for people with income around the cutoff of 150 percent of FPL in the post-reform period.

A statistic is constructed to quantitatively test the discontinuity, which is defined as $\theta_{diff} = \theta_{post} - \theta_{pre}$. θ_{post} is the log difference of the income density between the right and left limit of the cutoff in the post-reform period, and θ_{pre} is the log difference in pre-reform period. The estimation and reference of θ_{post} and θ_{pre} are developed by McCrary (2008). θ_{diff} is the difference between θ_{post} and θ_{pre}, representing the change of income discontinuity between the pre-reform and post-reform periods. A negative value of θ_{diff} represents a shift of income distribution from the right to the left of the tested income level. The standard deviation σ_{diff} is defined as $\sigma^2_{diff} = \sigma^2_{post} - \sigma^2_{pre}$, where σ_{post} and σ_{pre} are the standard deviation for

θ_{post} and θ_{pre}.[5]

Table 2 shows the estimation results. For the whole sample at 150 percent of FPL, θ_{05} is estimated as 0.047 with a standard deviation of 0.048, and θ_{08} is estimated as -0.186 with a standard deviation of 0.048. Therefore $\hat{\theta}_{diff}$ is -0.233 with standard deviation 0.096. The change of income discontinuity is significantly different from zero at 150 percent of FPL, and the income density shift from the right to the left of the cutoff after the implementation of the program. As is stated before, 150 percent of FPL is the first income cutoff in the subsidy schedule. This discontinuity is a similar finding as Saez (2010) who provides bunching evidence at the first kink point of the Earned Income Tax Credit. The 150 cutoff also falls between plans with zero and non-zero out-of-pocket premiums. The evidence of discontinuity suggests that the population are sensitive to the choices between free and non-free insurance plans.

Table 2 also displays the estimations at other three income cutoffs. The parameters $\hat{\theta}_{diff}$ are significantly different from zero at 300 percent of FPL, which is the cutoff falling between plans with the largest subsidy difference. The population located around this cutoff have the largest incentive to manipulate their income. The results do not suggest income manipulation at the other two cutoffs, the 200 and 250 percent of FPL.

I also test income manipulation at other income levels. If the income manipulation is indeed caused by the specific program, the discontinuity should be observed at and only at the cutoffs regulated by the subsidy schedule. Income discontinuity should not be found at other income levels. The estimation results are shown in Figure 4 and Figure 5. Figure 4 displays the results for $\hat{\theta}_{pre}$ and $\hat{\theta}_{post}$ in year 2005 and 2008, respectively, and Figure 5 displays the results for $\hat{\theta}_{diff}$ based on the estimations in pre- and post-reform periods. The x-axis indicates the income level as percent of FPL, from 50 to 500 percent of FPL, and the y-axis indicates the estimation of $\hat{\theta}$. The solid line reports the estimation results at every integer level of income, and the dashed lines show the 95 percent confidence interval.

[5]The definition is based on the assumption that samples in two periods are not correlated, since they are selected independently in different periods.

Figure 5 support the conclusion that the subsidized program causes income manipulation of the population. Significant income discontinuity is shown at the income levels of 150 and 300 percent of FPL, which are the income cutoffs according to the subsidy schedule. The negative values of $\hat{\theta}_{diff}$ indicate the shift of income density from the right to the left of the tested income levels. There is no significant negative discontinuity at other income levels. [6]

I also analyze the income manipulation for samples by working status and age. Figure 6 illustrates the estimation results on $\hat{\theta}_{diff}$ for wage workers and self-employed. The figures show that the income manipulation at the 300 percent of FPL is concentrated by wage workers, and the manipulation at the 150 percent of FPL is concentrated by self-employed. It is harder for wage workers to control their income, so the manipulation only happens at the cutoff with the greatest incentives. The manipulation only happens at the first cutoff for self-employed, which is a similar finding as Saez (2010) that the income distribution of self-employed bunches at the first kink point of the Earned Income Tax Credit.

For people with different ages, I expect to see a larger response for the old, who will have larger incentives to manipulate the income than the young. The old tend to be sicker than the young, so they will have higher values for insurance plans than the young. Figure 7 displays the estimation results. There are discontinuities at the cutoffs of 150 percent FPL and 300 percent FPL for both samples, and I find that the two groups behave similarly to each other.

Three types of robustness check are conducted to support the conclusion that the subsidized program causes income manipulation. First, the bandwidth of the kernel RD estimation is varied to check the sensitivity of the results. The bandwidth for the main analysis is the optimal bandwidth defined by McCrary (2008), and is around 150 percent FPL. Another two levels of bandwidth, 100 percent FPL and 50 percent FPL, are selected to estimate $\hat{\theta}_{diff}$, and the results are shown in Figure 8. I find that the discontinuities at 150 percent FPL and

[6] Significant positive discontinuities are found at several other income levels. The positive value means a shift of income from the left to the right of the tested level. Unfortunately, I do not have a plausible explanation on this trend of income change.

300 percent FPL are still significant in both cases.

Second, I change the sample year for the post-reform periods. The program is implemented in 2006, and the main results are based on the samples from year 2005 and 2008. Instead, I choose 2007 and 2009 as post-reform periods to estimate the discontinuity parameter θ_{diff}. The results are illustrated in Figure 9. The discontinuity at the 150 percent cutoff still exists but not significant. The discontinuity at the 300 percent FPL is significant in both tests.

Third, I estimate the same parameter using samples from Connecticut, a control state where the population has a similar demographic distribution as in Massachusetts. Figure 10 shows the results. There are several discontinuities around the income levels 100 percent FPL, 125 percent FPL, 150 percent FPL, and 300 percent FPL, which may be due to other policy changes between the two periods, and the magnitude of these discontinuities is smaller than that in Massachusetts.

4 Elasticity Estimation

In this section, I assume that the change of income all comes from the change of labor supply, and construct a structural model to estimate the labor supply elasticity with respect to wage rate. The methodology is largely based on the model developed by Saez (2010), and with two extensions. First, Saez (2010) observes a bunching pattern in the distribution of income and establishes a correspondence between the pattern and the elasticity. This approach requires a subjective setting on the bandwidth at which the bunching occurs. In my approach, I directly establish an MLE model, which eliminates subjective factors involved.

Second, Saez (2010) assumes that when agents choose their labor supply level, they are unaware of the income uncertainty they face, and hence choose the target income level exactly at the cutoff. At the same time, he argues that in reality there is an uncertainty that affects

the actual income the agents receive. In my model, I assume that people are aware of the income uncertainty and hence will manage the risk of not receiving the subsidy by further lowering their labor supplies. From the perspective of a researcher, I am able to detect the degree of income uncertainty in my model.

In the following part, Section 4.1 shows the model, Section 4.2 illustrates the estimation strategy, and Section 4.3 provides the estimation results.

4.1 Structural Model

There is a population of heterogeneous agents. Each agent i has an ability b_i. An agent has a utility function of two components, income I_i, and labor z_i. Her utility can be represented by a quasi-linear and iso-elastic function that has the same form as the utility function used by Saez (2010),

$$v_i(I_i, z_i) = I_i - \frac{b_i}{1 + \frac{1}{\varepsilon}} (\frac{z_i}{b_i})^{1+\frac{1}{\varepsilon}},$$

where ε is the labor supply elasticity.

Income comes from two potential sources: the wage income W_i, and the subsidy S_i:

$$I_i = W_i + S_i.$$

The expected wage income is proportional to labor, with wage rate w. A disturbance of e_i also contributes to the wage income. The total wage income is

$$W_i = wz_i + e_i,$$

where the error term e_i has normal distribution, $e_i \sim N(0, \sigma^2)$, and is i.i.d.

A subsidy a_i, depending on family characteristics, is granted when the wage income is below an income cutoff I^*:

$$S_i = \begin{cases} a_i & if\ W_i \leq I^* \\ 0 & if\ W_i > I^* \end{cases}.$$

Therefore the expected utility can be deduced as

$$Eu_i(z_i) = Ev_i(I_i(z_i), z_i) = wz_i + P(e_i \leq I^* - wz_i) \cdot a_i - \frac{b_i}{1+\frac{1}{\varepsilon}}(\frac{z_i}{b_i})^{1+\frac{1}{\epsilon}}.$$

When there is no subsidy, i.e., $a_i = 0$, the first-order condition (F.O.C.) of the expected utility is

$$\begin{aligned} w &= (1+\tfrac{1}{\varepsilon}) \cdot \tfrac{1}{b_i} \cdot \tfrac{b_i}{1+\frac{1}{\varepsilon}} \cdot (\tfrac{z_i}{b_i})^{\frac{1}{\epsilon}} \\ &= (\tfrac{z_i}{b_i})^{\frac{1}{\epsilon}} \end{aligned}. \tag{1}$$

Re-arranging equation (1) yields $\varepsilon = \frac{\partial \ln z_i}{\partial \ln w}$, which shows that ε is the elasticity of labor supply with respect to the wage rate.

I focus on the impact of subsidy to labor supply, so it is convenient to set $w = 1$. In this case, the labor supply is $z_i = b_i$, which means that people will make their effort levels equal to their abilities when there is no subsidy.

Where there is a subsidy, the utility function is deduced as

$$Eu_i(z_i) = Ev_i(I_i(z_i), z_i) = z_i + \Phi(\frac{I^* - z_i}{\sigma}) \cdot a_i - \frac{b_i}{1+\frac{1}{\varepsilon}}(\frac{z_i}{b_i})^{1+\frac{1}{\epsilon}}.$$

Maximize utility function using F.O.C., and it becomes

$$1 + (\phi(\frac{I^* - z_i}{\sigma})(-1)) \cdot a_i - \frac{b_i}{1+\frac{1}{\varepsilon}}(1+\frac{1}{\varepsilon})(\frac{z_i}{b_i})^{\frac{1}{\varepsilon}}\frac{1}{b_i} = 0$$

$$\Rightarrow 1 - \phi(\frac{I^* - z_i}{\sigma})a_i - (\frac{z_i}{b_i})^{\frac{1}{\varepsilon}} = 0. \tag{2}$$

The equation (2) illustrates that the optimal effort level z is determined jointly by

$(\varepsilon, \sigma, b, a, I^*)$. (ε, σ) are the parameters to be estimated, and I^* is the income cutoff of the subsidized program that is exogenous in the model. I assume that ε, σ and I^* are the same for all the population. The ability b and the subsidy a are family-specific characteristics. There is no explicit expression $z(b, a|\varepsilon, \sigma, I^*)$ that maximizes this utility function, but it can be numerically solved. I denote the optimal effort level as $z(b, a)$ for the convenience of displaying MLE estimation strategy in the next subsection.

4.2 Estimation Strategy

For an individual i with ability level b_i, she chooses the effort level $z(b_i, a)$, and the density at income level I_i is $\phi(\frac{I_i - z(b_i,a)}{\sigma})$. I assume the ability has a distribution $g(b)$, so the overall density across all ability levels is

$$f_i(I_i; g(\cdot), \sigma, \varepsilon) = \int_0^\infty g(b) \cdot \phi(\frac{I_i - z(b, a)}{\sigma}) db.$$

The log likelihood function for the whole population is

$$l(\sigma, \varepsilon, g(\cdot)|I) = \frac{1}{N} \sum_{i=1}^{N} \ln \int_0^\infty g(b) \cdot \phi(\frac{I_i - z(b, a)}{\sigma}) db.$$

In practice, it is hard to identify the continuous distribution of $g(\cdot)$. Instead, I assume that the ability is distributed over a set of discrete points $\{b_1, b_2, \cdots, b_j, \cdots, b_J\}$. The probability of being b_j is g_j, and I denote $z_j(a) = z(b_j, a)$ and $g = \{g_1, g_2, \cdots g_j, \cdots, g_J\}$. Hence the likelihood function is

$$l(\sigma, \varepsilon, g|I) = \frac{1}{N} \sum_{i=1}^{N} \ln \sum_{j=1}^{J} g_j \cdot \phi(\frac{I_i - z_j(a)}{\sigma}).$$

Among the people with eligible income, only a fraction, p, of the them are affected by the

program. Those who are not affected will choose the effort levels that equal to their abilities. The density of income for those people is $\phi(\frac{I_i - b_i}{\sigma})$. Therefore the likelihood function becomes

$$l(\sigma, \varepsilon, g|I) = \frac{1}{N}\sum_{i=1}^{N} \ln \sum_{j=1}^{J} g_j \cdot \left[p\phi(\frac{I_i - z_j(a)}{\sigma}) + (1-p)\phi(\frac{I_i - b_i}{\sigma}) \right]. \tag{3}$$

with constraints $\sigma > 0$ and $\varepsilon > 0$.

The distribution of ability $g(b)$ is estimated using the income distribution in the pre-reform periods when there is no subsidy. I assume that the distribution is stable over time. The labor supply elasticity ε and the standard deviation of income σ are then estimated based on estimated distribution of ability and the infomation in the post-reform period, including the distribution of income I, the subsidy a, and the fraction, p, of people who are affected by the program. Income distribution is directly observed from the data, the subsidies at different income cutoffs are the amounts discussed in section 2, and the fraction p is inferred as 27.8% using statistics from public reports. Details of the calculation on p is provided in Appendix A2.

4.3 Estimation Results

Table 3 displays the estimation results at each income cutoff for various samples: the whole population, wage workers, and self-employed. I include observations within 30 percent of FPL around the cutoff in each estimation. For example, samples with income between 120 and 180 percent of FPL are included when estimating parameters at the cutoff 150 percent of FPL. Column (1) shows the number of observation in each estimation. Column (2) provides the estimation results of the labor supply elasticity. I find that the elasticity is almost zero in all the scenarios, which means that the population is inelastic with respect to the change in wage rate.

Although the estimation of the elasticity is zero, it does not mean that people do not have incentive to manipulate their income. Figure 11 illustrates the income ranges affected by the program under different values of labor supply elasticity. People with income between the income cutoff I^* and the cutoff plus the subsidy $I^* + a$ will lower their income, even when the labor supply is inelastic. The elasticity affects people with income above $I^* + a$. The greater the elasticity is, the more people with income above $I^* + a$ will lower their income. The elasticity also affects the selection of the targeted effort level. The higher the elasticity, the lower the optimal effort will be chosen.

One explanation for the small elasticity is that the income manipulation largely comes from the population with income slightly above the cutoffs. While the benefits of controlling income are the same, people with greater income need to decrease their income more in order to be eligible for greater subsidy, hence they have fewer incentives to lower their income. In practice, individuals face other difficulties in controlling income, so it is possible that only those with large incentives have changed their income. This explains why I have observed clear evidence of income discontinuity and estimated small elasticity of labor supply.

Column (3) in Table 3 shows the estimation of the standard deviation of income. The results are around 0.1 for all the scenarios, which are interpreted as the standard deviation of income is about 0.1 percent of FPL. For a single person, the FPL is about $10,000, so the standard deviation is $10. The results suggest that the income levels are stable for low- and middle-income individuals, and the small variation would have little impacts on the income manipulation of the subsidized program.

5 Welfare Impact and Implications for the National Reform

In this section, I calculate the welfare loss due to the subsidized program, which is measured as the income decrease after the implementation of the program. The dollar value of the

reduced income, ΔI, is defined as $\Delta I = P \cdot f \cdot \bar{\delta}$, where P is the number of population falling in the affected income range who have incentive to lower their income, f is the fraction who indeed changed their income, and $\bar{\delta}$ is the average amount of reduced income. Table 4 displays the calculation process and the results. The total welfare loss due to the subsidized program is estimated as \$2.8 million in 2008. The details of the estimation are provided as follows.

Welfare loss happens only around the cutoffs of 150 and 300 percent of FPL, since there is no evidence of income manipulation at the other two cutoffs. Based on the affected income ranges, which are predicted by the parameters estimated from the structural model, the potential affected population, P, is estimated as 34,656 at the 150 cutoff and 118,047 at the 300 cutoff.

As is mentioned above, in practice people face difficulties in varying their income, such as they cannot change the working contract in short term. The information in Connecticut, a control state, and Massachusetts, the experimental state, is used to estimate the number of population who indeed changed their income after the implementation of the program. I calculate the percentage of population falling in the affected income range for the two states in both pre- and post-reform periods. The difference-in-difference percentage shows the fraction of the population who changed their income after the reform in Massachusetts. The results are 2.76 percent at the cutoff of 150 percent of FPL, and 2.83 percent at the 300 cutoff.

The average reduced income is determined by the affected income ranges. I assume that people uniformly distributed within the ranges, so the amount of the reduced income equals half of the length of the income range. For example, the affected range is 149.7 to 159.7 percent of FPL at the 150 cutoff, and the income change is 5 percent of FPL. The reduced income is then converted to dollar value. The conversion is affected by family size, since FPL is defined according to family structure. Without loss of generosity, I assume that half of the population come from single-person families, and half of them come from two-person

families. Under the assumption and the level of FPL, I calculate the average income decrease is $349.5 at the 150 cutoff and $751.3 at the 300 cutoff.

6 Conclusion and Discussion

My analysis has found substantial evidence of income discontinuity at the cutoffs of 150 percent FPL and 300 percent FPL of the subsidized program in the Massachusetts reform. The 150 percent FPL is the first cutoff and falls between plans charging enrollees zero and non-zero out-of-pocket premiums; this discontinuity is concentrated among the self-employed. The 300 percent FPL is the cutoff with the largest subsidy difference, and the effect is concentrated among the wage workers. By examining income discontinuity at other income levels as well as a control state, I conclude that the subsidized program causes income manipulation of the potential eligible population.

I construct a model with income uncertainty to estimate labor supply elasticity as well as income variation. The results suggest that the two factors have little impact on the behavioral response to the subsidized program. I simulate the impacted income range based on the estimation results, and assess the welfare loss due to the program. I find that the reduced income, possibly due to reduced labor supply, is about $2.8 million in 2008.

My model can be used to predict the response of the population to the subsidy schedule in the national reform, which has a similar structure as the schedule in the Massachusetts reform. Individuals receive two forms of subsidies: cost-sharing credits, which reduce individuals' payments on cost-sharing, and premium credits, which reduce the payments on insurance premiums. Cost-sharing has a similar piecewise schedule, which is expected to cause the response of income manipulation. For premium credit, subsidy is regulated proportional to income within range 133 to 400 percent of FPL, which eliminates population's incentive to manipulate income. However, the subsidy is discontinuous at the two income levels, 133 and

400 percent of FPL, which will create incentive of income manipulation.

The framework of the estimation on elasticity and income variation can be applied to any programs that generate nonlinear budget constraints, such as Medicaid. Income cutoffs exist in almost all welfare programs. When people are aware of the cutoff information, they will have incentive to manipulate their income. One valuable study could be to explore how much information the population are aware on the subsidized program, especially the regulation on cutoffs.

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Figure 1. Cost Difference for Enrollees in the Plans with the Lowest Premiums in Different Income Tiers

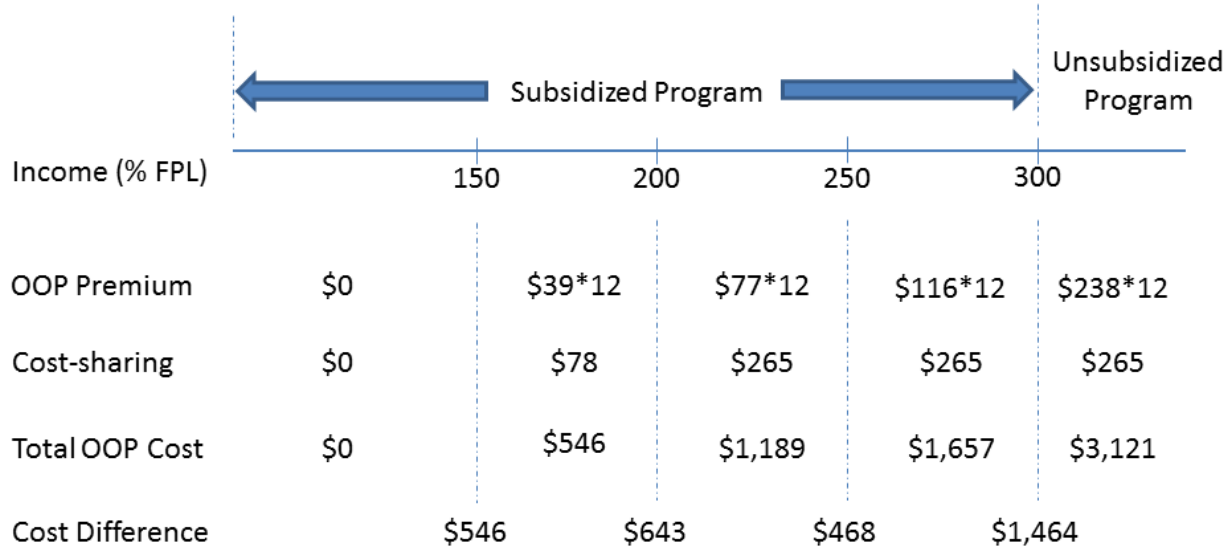
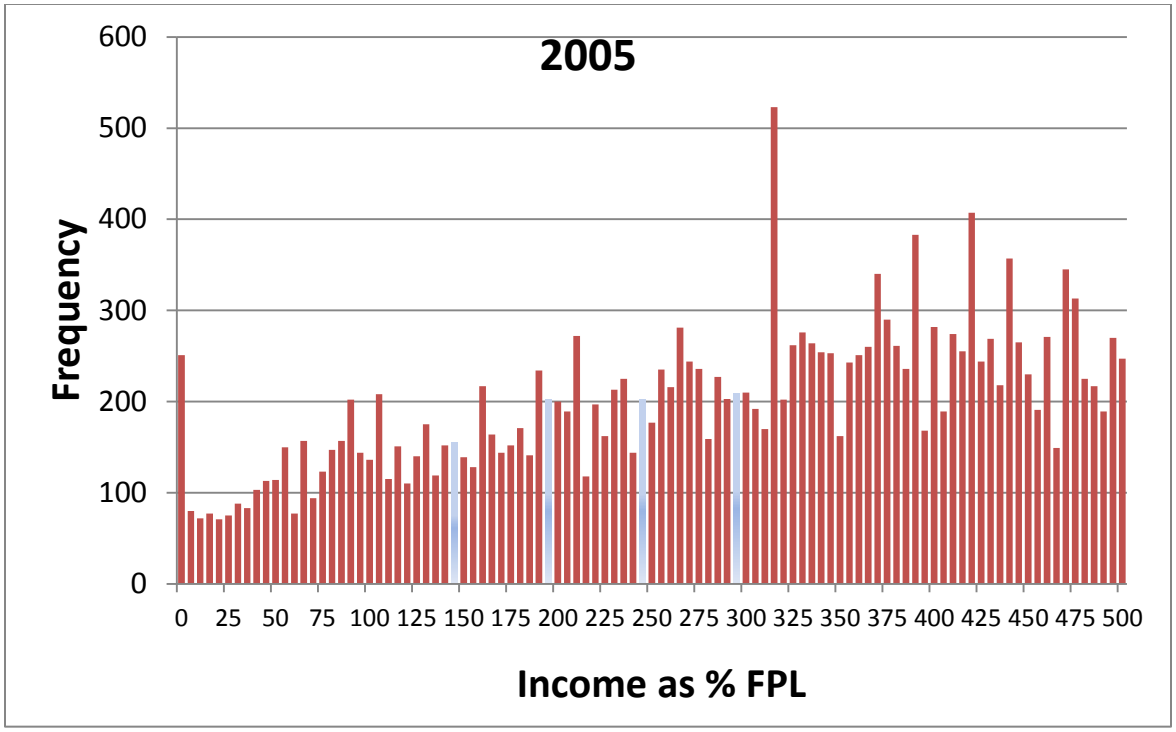


Figure 2. Income Distribution by FPL in 2005 and 2008



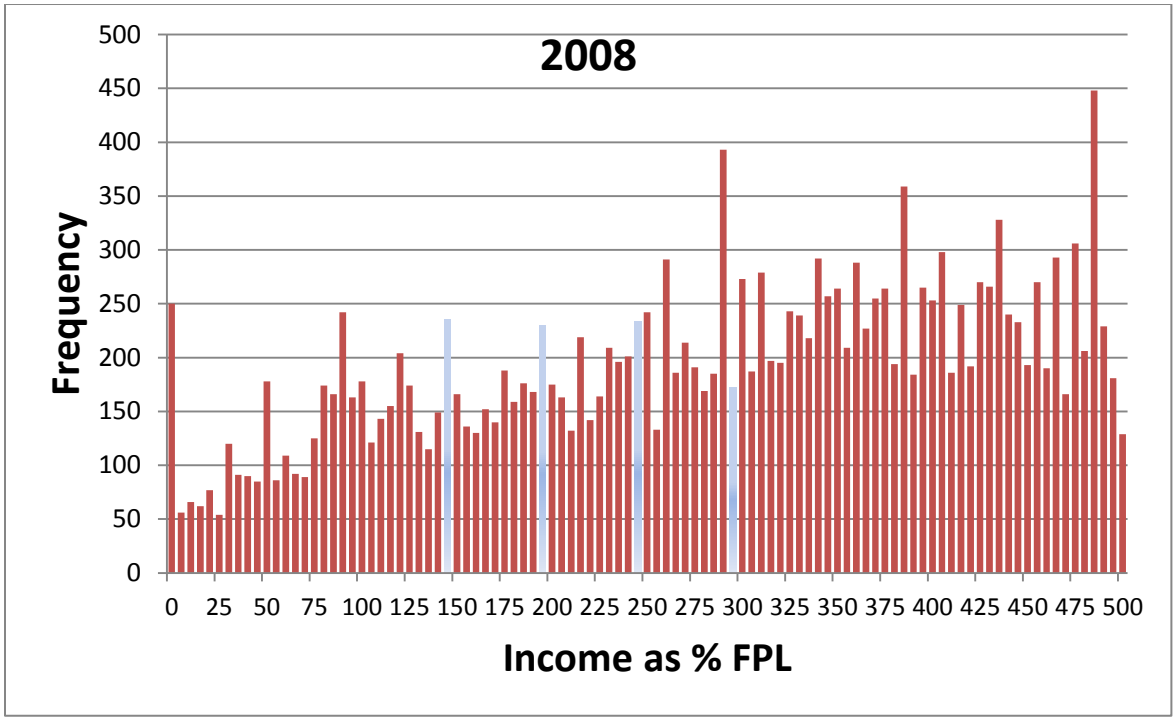


Figure 3. RD Estimation at the Cutoff of 150 percent FPL in 2005 and 2008

Figure 3A. 2008, binsize: 3.3, bandwidth: 143.7, $\hat{\theta}$: -0.186 (0.048)

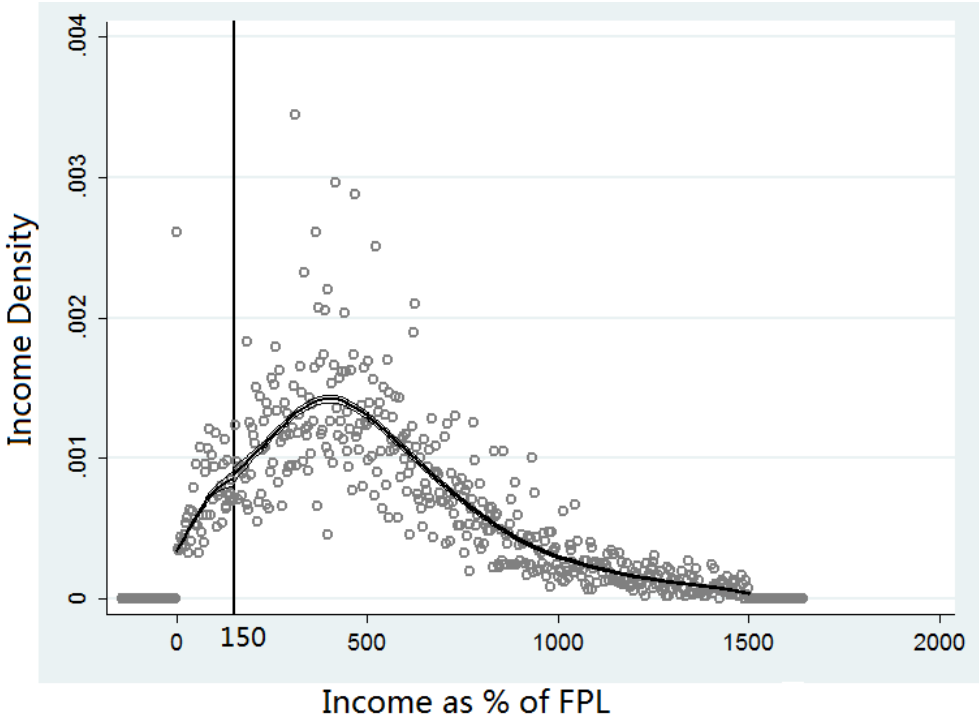
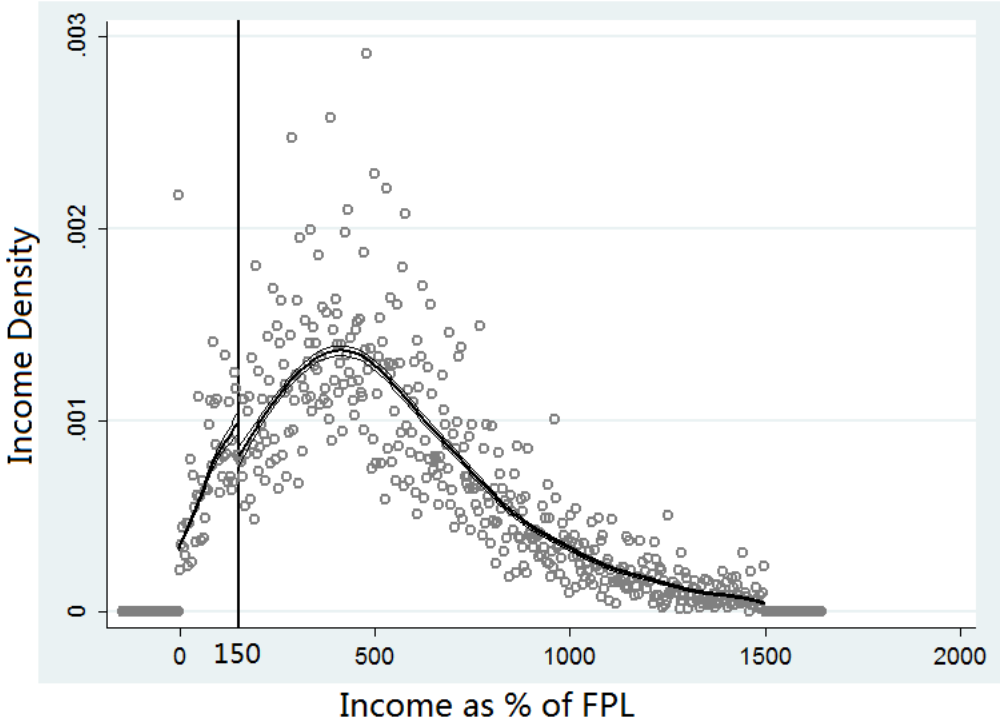


Figure 3B. 2005, binsize: 3.2, bandwidth: 141.7, $\hat{\theta}$: 0.047 (0.048)



Note: The standard deviation of $\hat{\theta}$ is shown in the parentheses.

Figure 4. Estimation Results on $\hat{\theta}_{pre}$ and $\hat{\theta}_{post}$ in 2005 and 2008

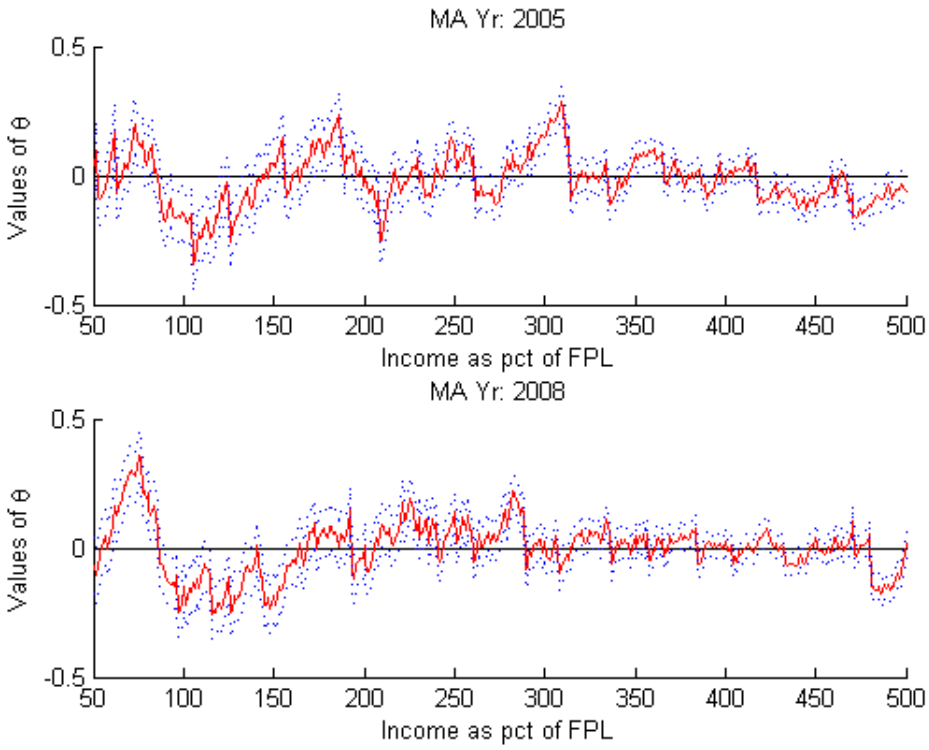


Figure 5. Estimation Results on $\hat{\theta}_{diff}$ between 2005 and 2008

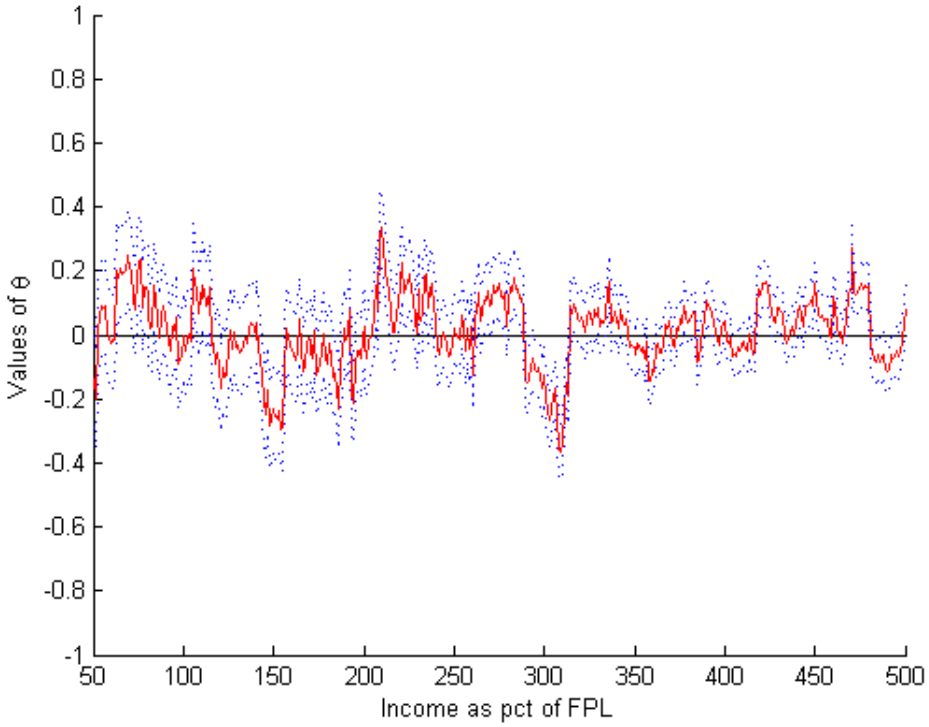


Figure 6. Estimation Results on $\hat{\theta}_{diff}$ between 2005 and 2008: Wage Workers Versus Self-employed

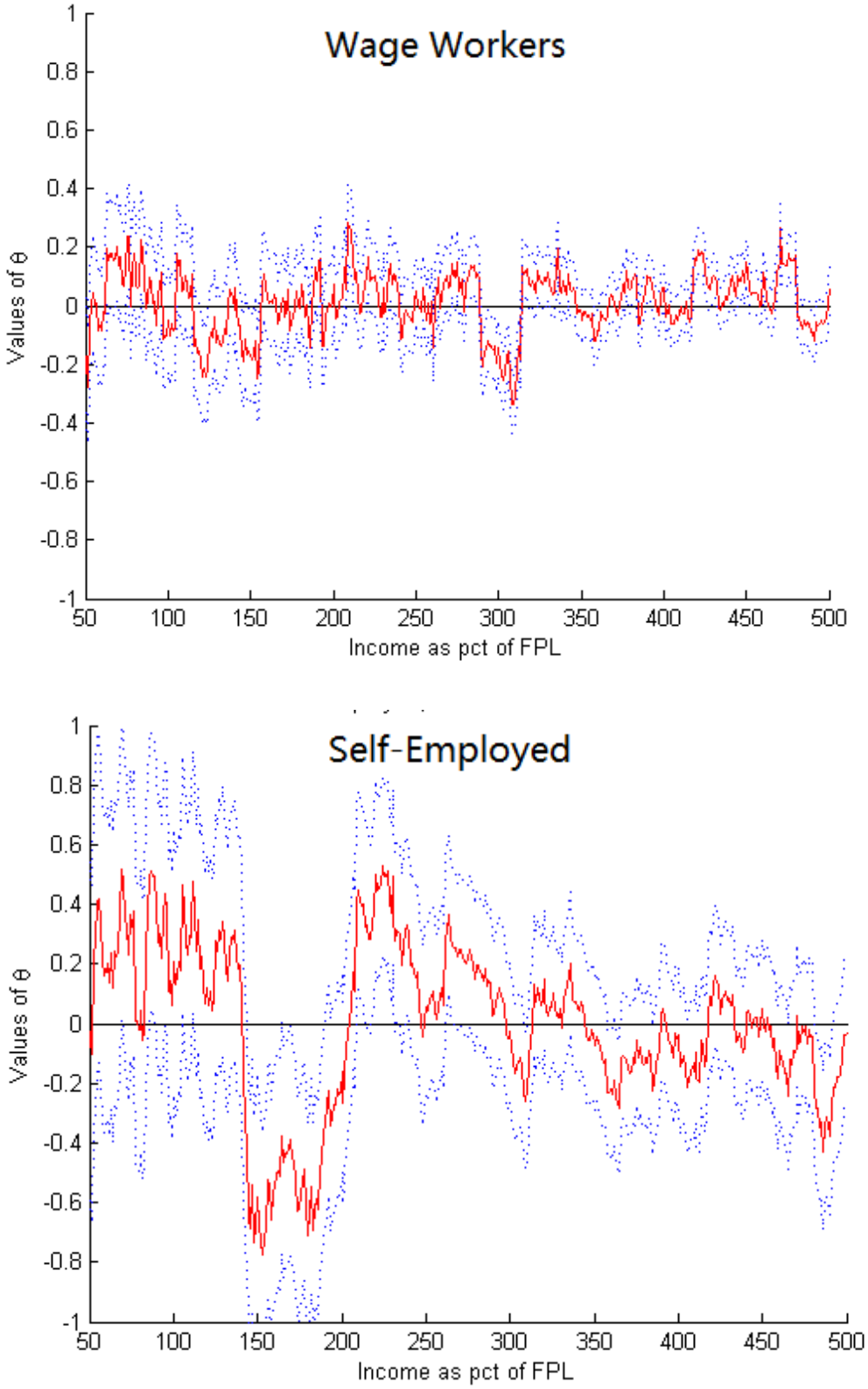


Figure 7. Estimation Results on $\hat{\theta}_{diff}$ between 2005 and 2008: Young (19-35) Versus Old (36-64)

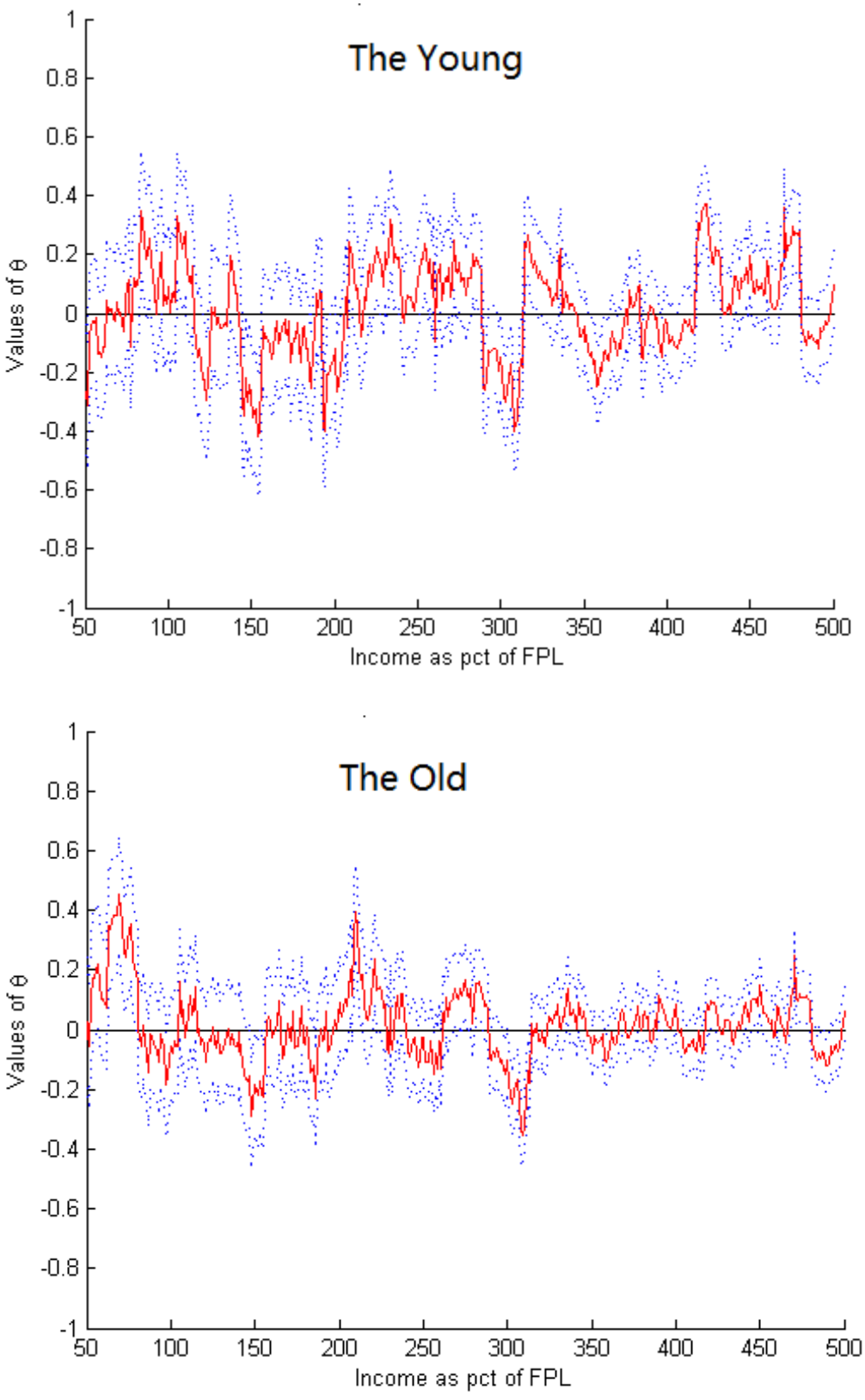
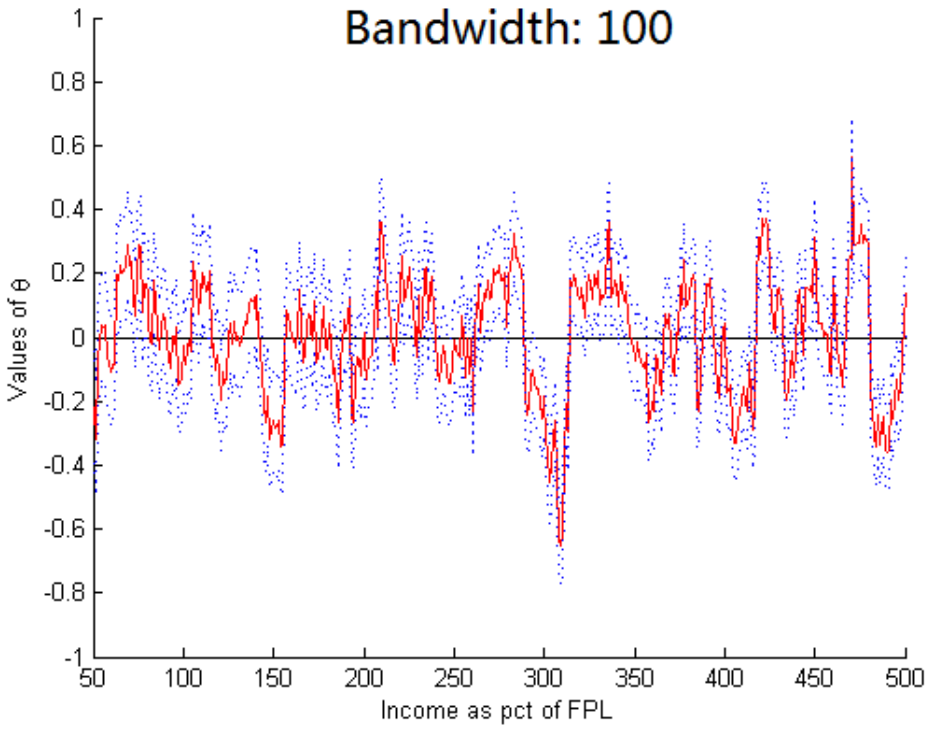


Figure 8. Estimation Results on $\hat{\theta}_{diff}$ with Bandwith 100 and 50 Percent of FPL



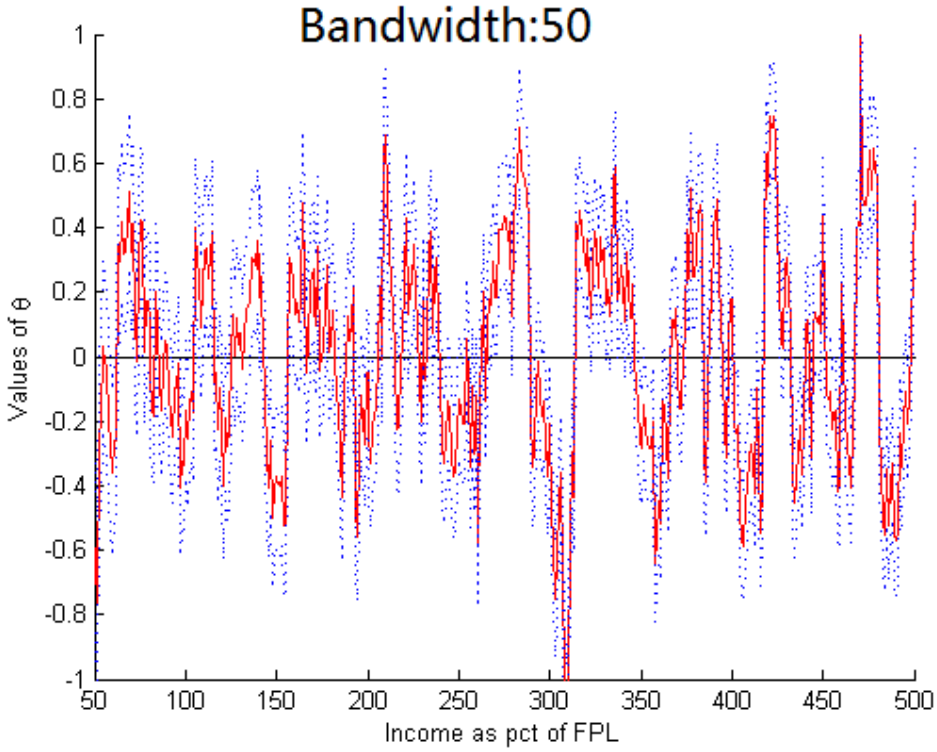
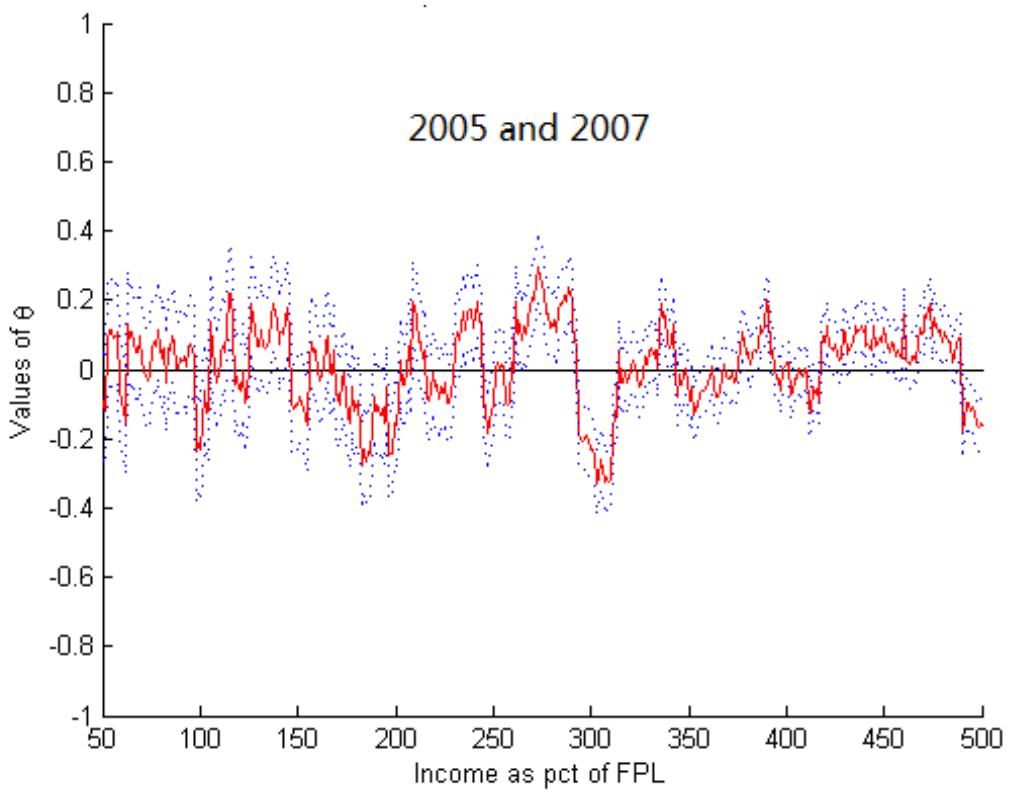


Figure 9. Estimation Results on $\hat{\theta}_{diff}$ between 2005 and 2007, and between 2005 and 2009



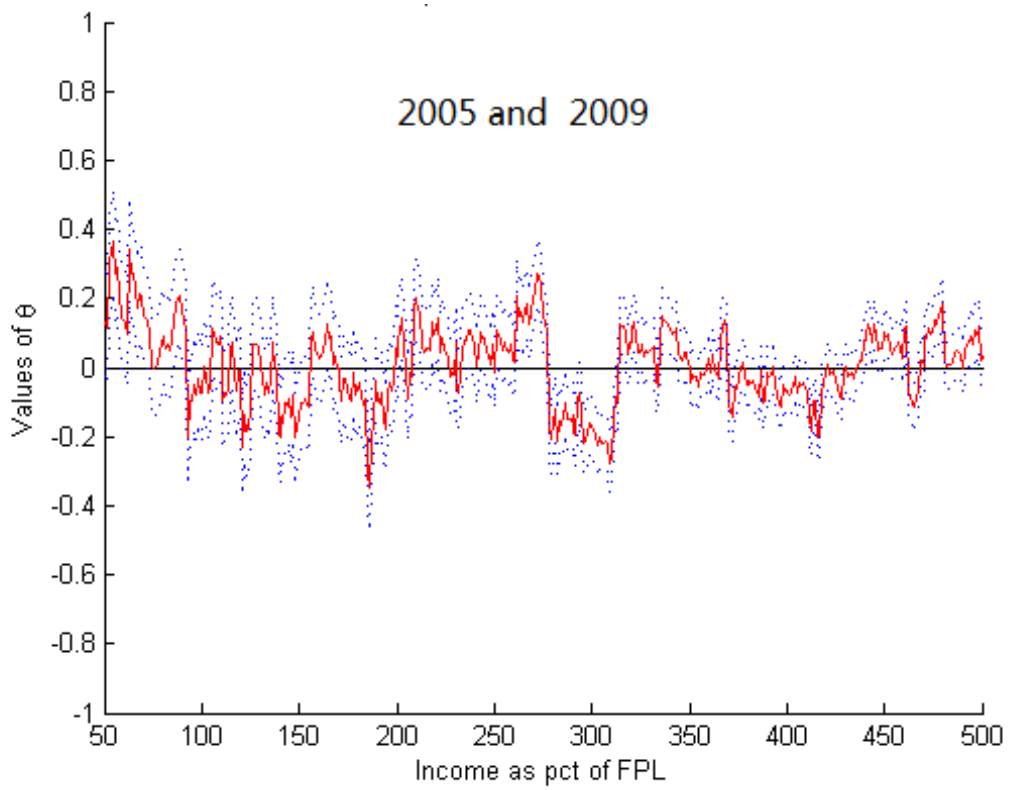


Figure 10. Estimation Results on $\hat{\theta}_{diff}$ between 2005 and 2008 in Connecticut

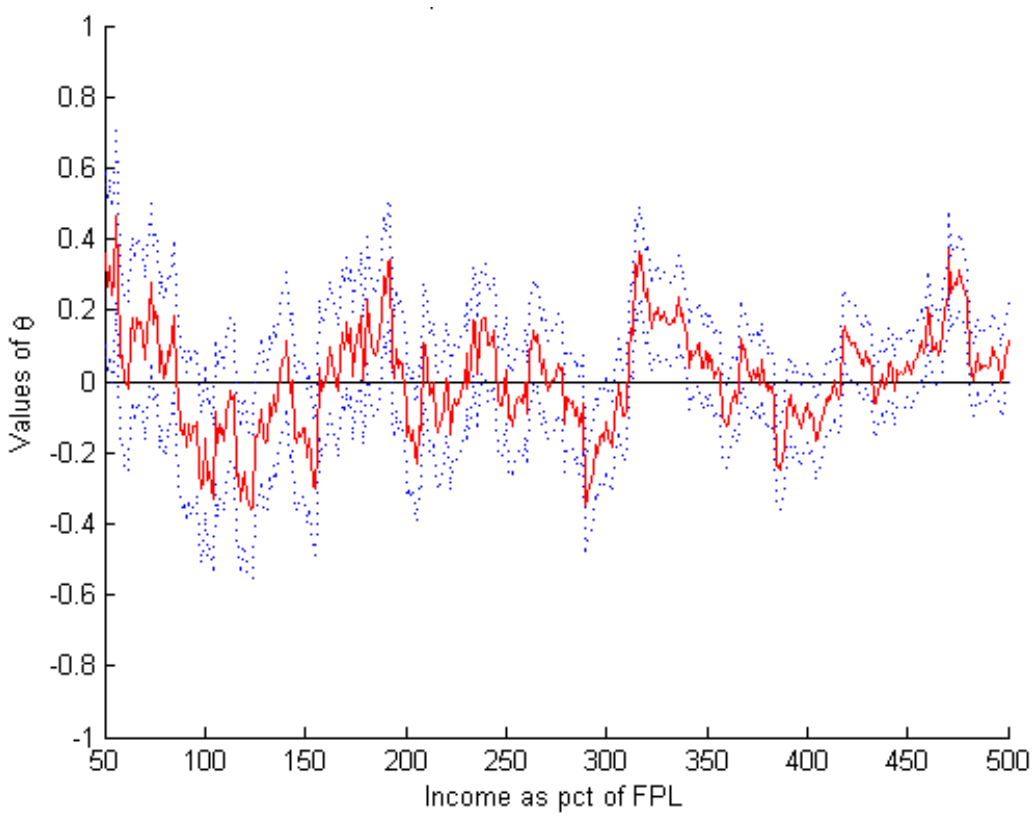


Figure 11. Income Ranges Affected by The Program under Different Values of Labor Supply Elasticity

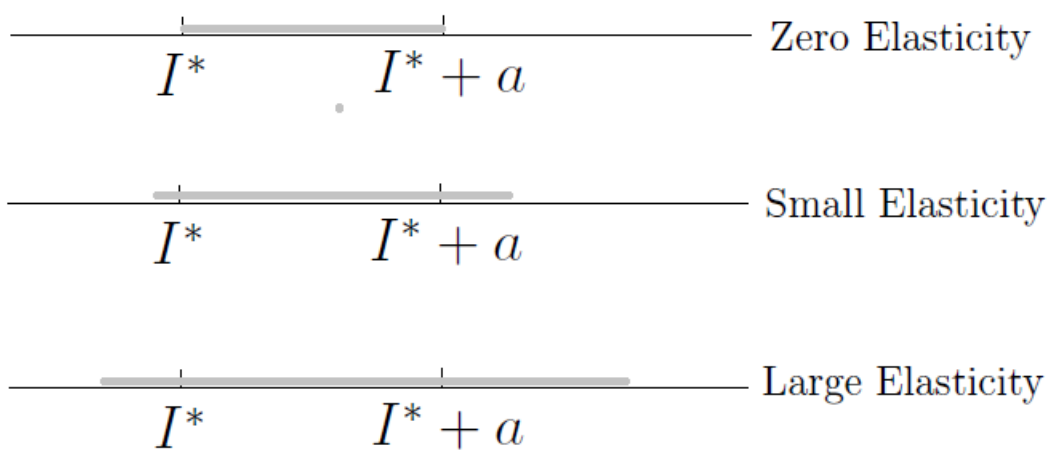


Table 1. Descriptive Statistics for the Population in 2005 and 2008

1A. 2005	All	Working Status		
		Wage Worker	Self-employed	Unemployed
N	36,358 *	30,047	3,227	3,084
% of the Whole Sample	100.0%	82.6%	8.9%	8.5%
Age				
Mean	42.2	41.4	46.3	46.7
Young (19-35)	31.4%	34.1%	16.1%	20.9%
Old (36-64)	68.6%	65.9%	83.9%	79.1%
Household Income				
Mean	$78,134 **	$80,181	$82,872	$53,229
Std. Dev.	$52,638	$51,418	$56,289	$53,932
Below 150% FPL	10.9%	8.8%	8.8%	33.9%
150-200% FPL	4.8%	4.5%	4.9%	8.2%
200-250% FPL	5.2%	4.9%	6.3%	7.1%
250-300% FPL	6.1%	6.0%	6.5%	7.0%
Above 300% FPL	72.9%	75.8%	73.5%	43.7%

1B. 2008	All	Working Status		
		Wage Worker	Self-employed	Unemployed
N	36,231	29,969	3,131	3,131
% of the Whole Sample	100.0%	82.7%	8.6%	8.6%
Age				
Mean	42.6	41.6	47.2	47.3
Young (19-35)	31.2%	34.2%	14.2%	19.7%
Old (36-64)	68.8%	65.8%	85.8%	80.3%
Household Income				
Mean	$86,387	$89,710	$86,138	$54,830
Std. Dev.	$58,700	$57,862	$60,327	$55,563
Below 150% FPL	11.4%	8.8%	11.5%	36.6%
150-200% FPL	4.6%	4.2%	4.8%	8.1%
200-250% FPL	5.2%	4.9%	6.4%	7.1%
250-300% FPL	6.1%	6.0%	6.6%	6.9%
Above 300% FPL	72.7%	76.1%	70.6%	41.4%

* The sample only includes population within age 19-64 and household income 0-1500% FPL.

** The calculation of the mean of household income in on the individual level, so we put higher weights on larger households than the calculation on the individual level.

Table 2. Estimation for $\hat{\theta}_{\text{pre}}$, $\hat{\theta}_{\text{post}}$, and $\hat{\theta}_{\text{diff}}$ at Four Income Cutoffs in Massachusetts

Cutoff (% FPL)	All Population			Self-employed			Wage Workers		
	2005	2008	Diff (08-05)	2005	2008	Diff (08-05)	2005	2008	Diff (08-05)
	$\hat{\theta}_{pre}$	$\hat{\theta}_{post}$	$\hat{\theta}_{diff}$	$\hat{\theta}_{pre}$	$\hat{\theta}_{post}$	$\hat{\theta}_{diff}$	$\hat{\theta}_{pre}$	$\hat{\theta}_{post}$	$\hat{\theta}_{diff}$
150	0.047	-0.186	-0.233**	0.260	-0.322	-0.582**	0.051	-0.116	-0.167
	(0.048)	(0.048)	(0.096)	(0.158	(0.139)	(0.297)	(0.056	(0.057)	(0.113)
200	-0.016	0.009	0.026	0.221	0.060	-0.161	-0.088	-0.014	0.074
	(0.044)	(0.045)	(0.088)	(0.117	(0.126)	(0.242)	(0.050	(0.050)	(0.100)
250	0.118	0.141	0.023	0.029	0.087	0.058	0.095	0.145	0.049
	(0.037)	(0.038)	(0.074)	(0.107	(0.103)	(0.209)	(0.041	(0.039)	(0.079)
300	0.148	0.022	-0.125*	0.104	0.077	-0.027	0.155	0.009	-0.146**
	(0.031)	(0.033)	(0.064)	(0.089	(0.081)	(0.170)	(0.034	(0.035)	(0.070)

Note: The standard deviation of $\hat{\theta}$ is shown in the parentheses.

* 10% significance, ** 5% significance.

Table 3. Estimation for the Elasticity and Income Variation

Income Cutoff	Population	N	Elasticity ε	Standard Deviation of Income σ
		(1)	(2)	(3)
150	All	3731	0.013 (0.001)	0.102 (0.002)
(120-180)	Wage Workers	2735	0.012 (0.001)	0.101 (0.003)
	Self-employed	316	0.011 (0.004)	0.075 (0.003)
200	All	4376	0.010 (0.000)	0.095 (0.001)
(170-230)	Wage Workers	3365	0.010 (0.001)	0.094 (0.001)
	Self-employed	428	0.010 (0.005)	0.081 (0.004)
250	All	4923	0.010 (0.003)	0.095 (0.002)
(220-280)	Wage Workers	3930	0.011 (0.000)	0.093 (0.002)
	Self-employed	485	0.012 (0.006)	0.080 (0.003)
300	All	5592	0.005 (0.005)	0.103 (0.002)
(270-330)	Wage Workers	4517	0.005 (0.006)	0.101 (0.003)
	Self-employed	554	0.019 (0.003)	0.083 (0.003)

Note: 1. Bootstrap standard deviation is shown in the parentheses.

2. Observations in 2005 and 2008 are included.

Table 4. The Results of Welfare Loss Estimation

	150 % FPL (149.7-159.7 % FPL)	300 % FPL (299.5-321.0 % FPL)	Total
P	34,656	118,047	
f	2.76%	2.83%	
$\bar{\delta}$	$349.5	$751.3	
Welfare Loss	$334,267	$2,509,891	$2,844,158

Appendix

A1. The Estimation of Plan Cost Difference among Different Income Tiers

The amount of cost-sharing is estimated on the benefit design and enrollees' expected health care costs. The plans for the 0-150 percent FPL have no copayment, zero insurance rates. The plans for the 150-200 percent FPL have $10 copayment for the visit to primary care physician, $18 copayment for the visit to the specialist, $50 copayment for the inpatient stay and zero insurance rates. The plans for the 200-250 percent FPL and 250-300 percent FPL have the same benefit design, which have $15 copayment for the visit to primary care physician, $22 copayment for the visit to the specialist, $250 copayment for the inpatient stay and zero insurance rate other than 10 percent for medical equipment. In addition, the plan varies on other characteristics too, such as the copayment on drug and the maximum out-of-pocket payment.

Plans total premium is $396 per month, which is equal to $4,752 per year. I assume a typical enrollee's total health care cost is $5,000 per year, and the health care service includes one visit to primary care physician, one visit to the specialist and one event of inpatient stay. Therefore the cost of cost-sharing for the enrollee is $0 for plans for 0-150 percent FPL, $78 for 150-200 percent FPL, and $265 for 200-300 percent FPL. I assume the amount of cost-sharing for the comparable unsubsidized plans is the same as the amount of the plans for 200-300 percent FPL.

A2. The Calculation on the Fraction of the Population Who Are Affected by The Program

I estimate the fraction of people who were enrolled in the subsidized program, CommCare, in the selected sample using statistics from the public reports. The total sample in the ACS in 2008 is 64,921, and the selected sample used in this analysis is 36,231, so 55.8 percent of the population is included. In 2008, the total population in Massachusetts is 6.469 million, and the selected sample represents 3.610 million. According to the reports published by the Division of Health Care Finance and Policy, as of December 31, 2008, there were 162,725 enrollees in the CommCare program, which equals 4.5 percent of the represented population. There was a total of 16.2 percent of individuals in the selected sample with a household income between 150 percent and 300 percent FPL. If all people with income below 150 percent FPL all enrolled in Medicaid, the percentage of people who were enrolled in the CommCare program in the selected sample is 27.8 percent.