Medicaid and the Labor Supply of Single Mothers: Implications for Health Care Reform*

Job Market Paper

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Abstract

The Patient Protection and Affordable Care Act (PPACA) substantially expands Medicaid eligibility and introduces health insurance subsidies. This health care reform changes work incentives since eligibility for these programs depends on income and earnings. To assess the employment effects of PPACA among single mothers, I estimate a structural model of labor supply of individuals who can obtain health insurance through their employer. Alternatively, they may be eligible for Medicaid coverage. I estimate the model exploiting exogenous variation in Medicaid policies across states and using data from the Medical Expenditure Panel Survey. Then I use the estimated preference parameters to simulate single mothers' employment choice under health care reform. The simulation results show that single mothers are about six percent more likely to participate in the labor force due to PPACA. They also increase their labor supply from part-time to full-time work by about five percent. Moreover, I find crowding-out of employer-sponsored health insurance of about 40 percent in this population. The value that single mothers place on PPACA benefits offsets the increased costs to the government, so the reform is welfare improving.

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1 Introduction

The health care reforms passed by Congress in 2010 (Patient Protection and Affordable Care Act, PPACA) have the potential to significantly affect employment among the low wage population. On the one hand, increased Medicaid eligibility and newly established health insurance subsidies will reduce the incentive to seek health insurance through employment. On the other hand, expanding the income cutoffs for eligibility will remove work disincentives for individuals who currently refrain from working because they are afraid to lose Medicaid eligibility. The effects of this law on work incentives for those marginally attached to the workforce are therefore ambiguous. At the same time, this population is important for policy makers because of its vulnerability and relative deprivation.

In this paper, I aim to determine the work incentive effects of the PPACA provisions that apply specifically to single mothers, a group that is characterized by low attachment to the labor force and will be particularly affected by these reforms. Single mothers and their children are also the main beneficiaries of Medicaid. In contrast to married women, they do not have the option to obtain health insurance coverage through the employer of their spouse. Moreover, they often lack the qualifications necessary to find a job with employer-sponsored health insurance (ESHI).

I estimate a structural model of labor supply that incorporates Medicaid and ESHI. In estimating the model, I rely on exogenous variation from recent expansions in Medicaid eligibility. After obtaining estimates of the preference parameters governing employment choice, I use them to simulate single mothers' labor supply and take-up of ESHI under health care reform. The structural approach allows me to analyze the effects of health insurance subsidies, a policy that has not yet been introduced at the national level.[1]

The existing literature on the effects of Medicaid on the labor supply of single mothers provides mixed evidence. Using data from the 1980s, Blank (1989) and Winkler (1991) find weak or no significant effects. Decker and Selck (2011) and Strumpf (2011) use variation generated by states introducing Medicaid in the 1960s and early 1970s and also find no impact on labor force participation. Meyer and Rosenbaum (2001) compare the labor supply effects of different welfare programs

[1] Another approach is to use local health care reforms that share some features with PPACA to estimate the employment effects of changes in health insurance availability. Examples include Colla et al. (2011) who use the employer mandate in San Francisco and Kolstad and Kowalski (2011) who exploit the Massachusetts reform. Finkelstein et al. (2011) analyze the Medicaid experiment carried out in Oregon, but do not consider labor market outcomes. Brügemann et al. (2011) analyze labor market consequences of health care reform in a general equilibrium framework.

and find that Medicaid has a relatively small effect compared to tax incentives. Moffitt and Wolfe (1992) and Dave et al. (2011) estimate that Medicaid lowers labor supply among women with large medical needs and pregnant women, respectively. In contrast, Yelowitz (1995) finds that increased Medicaid eligibility in the late 1980s and early 1990s reduced work disincentives and led to an increase in labor force participation. In contrast to my paper, these studies employ a reduced-form approach, only consider the labor force participation decision, and do not treat ESHI coverage as a choice variables.

I model take-up of ESHI jointly with the labor supply decision and let both depend on Medicaid availability, while the literature on health insurance and labor supply considers Medicaid and ESHI separately.[2] Potential ESHI coverage, however, may have an impact on the direction of the employment effect of Medicaid. On the one hand, many low-income individuals are not qualified for jobs that provide health benefits. Moreover, they are only eligible for Medicaid if their income falls below the relevant threshold, which induces work disincentives. Expanding Medicaid eligibility or introducing health insurance subsidies relaxes this constraint and potentially increases labor supply. On the other hand, if the income threshold increases sufficiently, workers with ESHI coverage may become eligible for Medicaid or subsidies. If these alternatives are cheaper or more generous than ESHI, PPACA may lead to crowding-out of ESHI.[3,4] However, none of the existing studies treats ESHI coverage explicitly as a choice variable although about a third of single mothers are covered by ESHI (Yelowitz, 1995).[5]

While the studies cited above only consider the participation decision, this paper allows for both full-time and part-time employment.[6] As I argue in the previous paragraph, workers with low initial labor supply might increase their hours when the Medicaid eligibility threshold increases. Others might work full-time prior to health care reform in order to qualify for ESHI coverage. Introducing health insurance subsidies allows these individual to reduce their labor supply and drop ESHI coverage while obtaining subsidized health insurance. Therefore, not allowing for an intensive margin would mask these changes in labor supply.

[2]Currie and Madrian (1999), Gruber (2000), and Gruber and Madrian (2002) survey studies in both areas.

[3]For example, Cutler and Gruber (1996) estimate crowding-out of ESHI of about 50 percent due to Medicaid expansions.

[4]Medicaid expansions may also reduce job lock. Workers who hold a job that is not an ideal match only to obtain ESHI coverage may be able to switch to a more productive match if they become eligible for Medicaid (Hamersma and Kim, 2009).

[5]Moffitt and Wolfe (1992) and Meyer and Rosenbaum (2000) account for ESHI benefits, but assume that all workers are covered instead of treating ESHI coverage as individuals' choice.

[6]The studies by Keane and Moffitt (1998) on the effects of different welfare programs on labor supply and by Buchmueller and Valletta (1999) on the impact of ESHI on the labor supply of married women are two exceptions.

I also contribute to the literature by allowing individuals to differ in how much they value health insurance. Most prior studies on health insurance and labor market outcomes do not explicitly account for heterogeneity in the demand for health insurance coverage. By contrast, I allow the demand for health insurance to vary with individual health. For example, a healthy person might change her behavior less in response to Medicaid expansions than someone with chronic medical conditions that require expensive health care. To address individual valuation of health insurance coverage, Moffitt and Wolfe (1992) and Keane and Moffitt (1998) match data on health expenditures and labor market outcomes from two different sources. In contrast, the data I use contain information on both, which makes matching unnecessary.

To estimate the model of labor supply, I draw on changes in Medicaid policies after the 1996 welfare reforms, a source of identifying variation that almost no study has used.[7] These expansions mostly affected parents while earlier expansions only increased the eligibility of children and pregnant women. States also gained the opportunity to increase parental Medicaid eligibility beyond federal minimum requirements, thereby introducing more variation. Since PPACA extends Medicaid eligibility to even broader groups, the analysis of the more current Medicaid expansions is of particular policy interest. Moreover, this allows for more realistic policy simulations since some states already have Medicaid thresholds that are as high as the one specified by health care reform.

Hence, my contributions are fourfold. I treat Medicaid and ESHI coverage in a unified framework and distinguish between full-time and part-time work. Moreover, I allow for heterogeneity in individuals' valuation of health insurance and use data on recent policy changes.

The estimated preference parameters indicate that single mothers with medical conditions are significantly more likely not to work in order to be eligible for Medicaid or to work full-time with ESHI. Hence, these women benefit particularly from PPACA since it allows them to enter the labor force and to work in jobs without ESHI coverage. The simulation results show that health care reform increases labor force participation among single mothers by about six percent. Moreover, labor supply at the intensive margin grows by about five percent. Finally, health care reform leads to crowding-out of ESHI of about 40 percent in this population. These results are heterogeneous across subgroups, however, with single mothers with medical conditions reacting most strongly to the reform, as expected based on the preference parameter estimates. The welfare implications of

[7] In the only paper to date exploiting the variation in parental Medicaid thresholds after 1996, Hamersma and Kim (2009) show that expanding Medicaid eligibility reduces job lock among unmarried women.

the reform are positive since individuals are willing to give up more consumption on average than the reform costs.

The paper is organized as follows. In Section 2, I describe current Medicaid policies and the relevant provisions of the recent health care reform. I develop a labor supply model with health insurance in Section 3. Then I discuss my estimation strategy in Section 4 and describe the data used in the estimation in Section 5. Section 6 contains the estimation results and in Section 7, I discuss the policy simulation. Finally, Section 8 concludes.

2 Policy Background

In this section, I describe the relevant policy background regarding Medicaid and health care reform. I also highlight how variation in existing Medicaid rules helps to identify labor supply effects and explain the advantages and limitations of focusing the analysis on single mothers.

2.1 Current Medicaid Policies

Medicaid is the largest public health insurance program for working-age adults and children in the U.S., currently providing virtually free health care to 28 million children and 13 million parents in low-income households.[8] States administer their own Medicaid programs under broad guidelines set forth by the Centers for Medicare & Medicaid Services (CMS). In particular, each state can expand upon the minimum levels of Medicaid eligibility that are defined by CMS (Iglehart, 1999). Therefore, the rules governing eligibility vary considerably between states.

By contrast, federal requirements regarding coverage of services are more extensive and the Medicaid programs are more homogeneous across states in the services covered. Mandatory services include hospital stays, physician care, laboratory and radiographic services, and preventive services (Iglehart, 1999). Federal law also prohibits excluding preexisting conditions or imposing waiting periods for coverage (Rosenbaum, 2002). There is also almost no cost sharing. Overall, Medicaid provides more generous coverage than Medicare and many private health plans.

On the other hand, physician reimbursement is lower for Medicaid patients than for those covered by Medicare or private health insurance.[9] Therefore medical providers are less willing

[8]Centers for Medicare & Medicaid Services, Medicare & Medicaid Statistical Supplement 2010 Edition, https://www.cms.gov/MedicareMedicaidStatSupp/09_2010.asp, Table 13.4.

[9]For example, Zuckerman et al. (2009) find that Medicaid reimbursement rates are on average 30 percent lower than Medicare rates.

to treat Medicaid patients, which limits access to health care. For example, over one third of physicians in small private practices did not accept Medicaid patients in 2005 (Iglehart, 2007). In sum, Medicaid provides very generous health care coverage, but restricts health care access compared to private health plans.

Historically, Medicaid eligibility was tied to welfare receipt. Therefore, most working parents did not qualify for public health insurance. A series of reforms has weakened the link between Medicaid and welfare, first for children and pregnant women starting in the mid-1980s and continuing for parents in the mid-1990s. In particular, the 1996 Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) enabled states to set Medicaid eligibility thresholds for parents independent of welfare rules. In this paper, I focus on the post-1996 changes in Medicaid eligibility. Before the welfare reform, there was no difference between eligibility for parental Medicaid and welfare, making it difficult to identify their separate effects in this period. Moreover, the eligibility thresholds for parental Medicaid in the post-1996 period are higher and therefore more comparable to the Medicaid threshold enacted by health care reform (see Section 2.2).

Figure 1 shows the development of Medicaid enrollment and spending for low-income adults and children between 1980 and 2008. Enrollment of children first increases significantly in the late 1980s when states started to expand eligibility for this group. However, only after the 1996 welfare reform did eligibility for parental Medicaid increase significantly. Enrollment of children continued to increase after 1996. Parental enrollment almost doubled since 1996 (from seven to 13 million), while child enrollment increased from 17 to 28 million over this period. Spending for parental Medicaid increased even more steeply than enrollment in this group.

Children, their parents, and pregnant women are eligible for Medicaid if family income falls below a threshold that varies by state.[10] These thresholds are often expressed as a percentage of the federal poverty line (FPL), which varies with family size. The minimum requirements set by the federal government differ between Medicaid for children and pregnant women and parental Medicaid. For example, federal regulation ensures that children and pregnant women are eligible if family income falls below 133 percent of the FPL. In contrast, there is no federal minimum level for parental Medicaid (Rosenbaum, 2009).[11]

[10] Childless adults are generally not eligible for Medicaid.

[11] In addition to income thresholds, asset tests were prevalent in determining Medicaid eligibility, but have been abolished in many states in recent years in an effort to simplify the application process. In 2009, 46 states did not require asset tests for children and 23 did not require them for parental Medicaid (Cohen Ross and Marks, 2009). Since there is no information on households' assets in the Medical Expenditure Panel Survey, the data set used in

This income test for Medicaid eligibility induces work disincentives. Families whose income exceeds the respective threshold by only one dollar lose eligibility. Since Medicaid is currently the only available source of public health insurance and ESHI is often not offered to low-wage workers, this means that most individuals are uninsured when they become ineligible for Medicaid. The sharp drop in benefits is also known as the Medicaid "notch" (Yelowitz, 1995). This "notch" leads to a strong incentive to reduce labor supply in order to keep earnings below the pertinent threshold. How much labor supply has to be reduced to stay eligible differs by state.

Starting in 1996 with PRWORA, many states have made use of the increased opportunity to increase Medicaid thresholds above the minimum requirements. Figure 2 shows the overall increase and dispersion of monthly income eligibility thresholds for some exemplary states for the years 1996 to 2007.[12] Some states did not change the threshold at all or even reduced it slightly (e.g., Texas), whereas others increased them by many times the initial value (e.g., District of Columbia, from about $500 to about $2500). Between these two extremes, Figure 2 shows several different patterns. For example, New York increased its Medicaid eligibility threshold in several steps from from about $500 to almost $2000, and Rhode Island shows an overall increasing trend with a sizable drop in eligibility in the middle of this time period.

Figure 2 illustrates the variation I use to identify the labor supply response to changes in Medicaid eligibility. There is variation in the income eligibility threshold for parental Medicaid across states and within states across time. Hence, I can compare single mothers residing in different states at different points in time and attribute differences in labor supply to differences in Medicaid eligibility conditional on other observables. I further discuss the identification strategy in Section 4.5.

2.2 The Patient Protection and Affordable Care Act

The components of the Patient Protection and Affordable Care Act (PPACA), which President Obama signed into law on March 23, 2010, can be classified into two major categories. First, it requires individuals to obtain health insurance coverage (individual mandate) and firms to provide it to their employees.[13] Second, it substantially expands Medicaid eligibility and provides health

this paper, I ignore asset tests for Medicaid eligibility completely. This is a reasonable simplification, in particular for children's Medicaid.

[12] I am grateful to Sarah Hamersma for sharing state-level eligibility thresholds for parental Medicaid with me.

[13] Both individuals and firms have the option to pay penalties if they do not take up and provide health insurance, respectively.

insurance subsidies to help low-income individuals comply with the insurance mandate. In this section, I focus on Medicaid expansions and subsidies since I simulate the effects of these provisions only.

In contrast to current Medicaid rules, citizens and legal residents below the age of 65 will be eligible for Medicaid starting in 2014, provided that family income does not exceed 138 percent of the FPL.[14,15] Childless individuals, who are not eligible for Medicaid under current rules, gain access to public health insurance through this expansion. In addition, the new law amounts to an eligibility expansion for parents and older children in many states. Forty-one states had Medicaid eligibility thresholds above 133 percent of the FPL for children under six in 2009, but only 24 states covered older children above that level (Cohen Ross and Marks, 2009). For working parents, Medicaid eligibility thresholds exceeded 133 percent in only 12 states (Rosenbaum, 2009). In addition, PPACA abolishes asset tests in the states where they are still applied. States that had Medicaid thresholds above 133 percent of the FPL in place in March 2010 cannot lower them before 2014 (for adults) and 2019 (for children).

Since childless adults will experience the largest increase in Medicaid availability, it would be important to analyze how they change their labor supply in response to this reform. However, these individuals are currently not eligible for Medicaid irrespective of their income. Since eligibility does not vary in this group, it is difficult to estimate the effect of Medicaid expansions on the labor supply of childless individuals and to simulate their employment choices under health care reform. Childless individuals probably make different employment decisions than single mothers so that I cannot extrapolate from the latter to the former.

Moreover, single mothers are an important group when it comes to Medicaid and its effects on labor supply. Since they are not able to obtain health insurance through a spouse, they rely more heavily on public health insurance options and are at a greater risk of being uninsured than married women. Therefore it is particularly policy relevant to analyze whether single mothers increase or reduce their labor supply due to health care reform.

Figure 3 shows population weighted parental Medicaid thresholds for a family of three for the years 1996 to 2007 in all states. Over this time period, very few states had thresholds above 138

[14] The official threshold will be 133 percent of the FPL, but there is a special adjustment of five percentage points, which effectively brings the threshold to 138 percent (Kaiser Family Foundation, 2010a).

[15] In 2011, 138 percent of the FPL amounts to about $25,600 for a family of three.

percent of the FPL.[16] This implies that the current variation in the data includes the new Medicaid threshold. Predicting employment choice under health care reform with this data will consequently not be completely out-of-sample.

In addition to expanding Medicaid eligibility, PPACA introduces subsidies for individuals who earn up to 400 percent of the FPL.[17] Individuals whose income falls below this threshold can purchase coverage on newly established Health Benefit Exchanges at premiums that are limited to a percentage of their income. The income percentage that individual have to pay at most for their coverage increases on a sliding scale as shown in Table 1 (Kaiser Family Foundation, 2010b). Subsidized health plans are limited to the silver plan with the second lowest cost in each state.[18] However, these subsidies are not available to individuals who are covered by ESHI. Since PPACA introduces subsidized health insurance for individuals and families in a wide range of the income distribution, this reform constitutes a substantial policy change.

Income range as % of FPL	HI premium limit as % of income
< 133	2
$133 - 150$	$3 - 4$
$150 - 200$	$4 - 6.3$
$200 - 250$	$6.3 - 8.05$
$250 - 300$	$8.05 - 9.5$
$300 - 400$	9.5

Table 1: **Health Insurance Subsidies Under PPACA**

Policy makers are aware that PPACA can have important consequences for the labor market. The Congressional Budget Office (2011) estimates, for instance, that health care reform will lead to a small overall decrease in labor supply.[19] This report argues that the positive income effect of Medicaid expansions and the introduction of subsidies will decrease work incentives. On the other hand, an increase in Medicaid eligibility thresholds can also lead to an increase in labor supply since the Medicaid "notch" shifts up. Moreover, subsidies will be available when individuals become ineligible for Medicaid, which weakens the disincentive to earn above this threshold. In sum, the CBO predicts employment to fall by 800,000 by 2021 relative to the status quo if labor

[16] Among the most populous states, some have Medicaid thresholds above 138 percent. For example, the thresholds in California and New York are around 150 percent of the FPL.

[17] For a family of three, 400 percent of the FPL is about $74,000.

[18] Health plans that are available on Health Benefit Exchanges are classified into bronze, silver, gold, and platinum plans according to their cost sharing. Silver plans cover essential health benefits and cover 70 percent of costs.

[19] See also Congressional Budget Office (2009) for a general discussion of the labor market effects of health care reform.

supply only changes at the extensive margin (Congressional Budget Office, 2011, p. 31). This report does not give any estimates for subpopulations, so I cannot directly compare this number to my simulation results. As discussed above, I also cannot extend my analysis to the general population, in particular not to childless individuals. However, I will revisit the CBO's prediction when I discuss my simulation results and compare it to the employment change among single mothers that is based on my empirical results.

3 Theoretical Model

In this section, I develop a discrete static model of labor supply with ESHI and Medicaid. The model serves as a framework for estimating and simulating the impact of Medicaid expansions on the labor supply of single mothers.

Agents face a static labor supply decision.[20] Each period, they receive three job offers, which are characterized by hours worked, a wage, and whether or not the job includes health benefits.[21] Agents can choose between one part-time offer and two full-time offers, one of which includes ESHI. Health benefits are not available for part-time jobs since most employers do not offer ESHI to their part-time workers. Weekly hours are 20 for part-time jobs and 40 for full-time jobs. The offered wage may differ by whether the offer includes ESHI. If an agent does not accept any of the three offers, she does not work for that period.

Individuals derive utility from per capita consumption, leisure (measured as disutility from hours worked), and health insurance coverage for themselves and their children.[22] Hence, utility of individual i in time period t when choosing either non-work ($j = n$), part-time employment ($j = p$), full-time employment without ESHI ($j = f_0$), or full-time employment with ESHI ($j = f_1$) is

$$U_{itj} = U\left(\tilde{C}_{itj}, H_{itj}, I^P_{itj}, I^K_{itj}; Z^u_i\right), \tag{1}$$

where $\tilde{C}_{itj}$ is per capita consumption, $H_{itj} = \{0, 20, 40\}$ is hours worked, and I^P_{itj} and I^K_{itj} are indicators for mothers' (indicated by P as in parental) and children's (K as in kids) health insurance

[20] Although the model is static, I use panel data to estimate it. Therefore, the time subscript t appears throughout this section.

[21] I do not model the probability of receiving an offer. However, a low wage draw leads individuals to decline an employment offer and is therefore equivalent to receiving an offer with a lower probability (see equation (7) below).

[22] The family consisting of a single mother and her children is treated as a unit, i.e. the family is a unitary household in which the mothers are the only decision-makers (e.g., Bergstrom, 1997).

coverage, respectively. Z_i^u is a vector of individual characteristics that do not change over time and affect preferences. Since there are economies of scale in consumption, I use an equivalence scale of the form

$$\tilde{C}_{itj} = \frac{C_{itj}}{1 + \sqrt{NK_{it}}}, \tag{2}$$

where C_{itj} is total family consumption and NK_{it} is the number of children.

The family's budget constraint is

$$C_{itj} + E_{itj}^P + E_{itj}^K + prem_{it} \times I_{itj}^S = w_{itj}H_{itj} + T_{it}\left(w_{itj}H_{itj}\right), \tag{3}$$

where E_{itj}^P and E_{itj}^K are out-of-pocket medical expenditure of the mother and her children, respectively, $prem_{it}$ is the part of the ESHI premium paid by the employee if she obtains ESHI coverage ($I_{itj}^S = 1$), w_{itj} is the wage in alternative j, and $T_{it}\left(w_{itj}H_{itj}\right)$ is the sum of government transfers (welfare, food stamps, payroll and income taxes, and the Earned Income Tax Credit) as a function of earnings. Each period individuals choose the alternative that yields the highest utility according to the utility function (1) subject to the budget constraint (3).

Health insurance is valued because it reduces out-of-pocket medical expenditures. Beyond that, individuals also derive utility from health insurance since it has a positive effect on health and reduces the risk a family faces. I assume that the two sources for health insurance coverage, ESHI and Medicaid ($I_{itj}^{M,h}, h = P, K$), are perfect substitutes:

$$I_{itj}^h = \max\left\{I_{itj}^S, I_{itj}^{M,h}\right\}, h = P, K. \tag{4}$$

Medical services covered by ESHI and Medicaid are roughly comparable. Medicaid covers services that may be not available under some low-cost ESHI plans. On the other hand, Medicaid reduces access to health care due to lower provider reimbursement rates. Therefore, the simplifying assumption implied by equation (4) is reasonable.

Mothers and their children are covered by ESHI if the mother works full-time with health benefits, i.e. $I_{itj}^S = \mathbf{1}\{j = f_1\}$. I assume that mothers who work full-time with ESHI coverage obtain health benefits for both themselves and their children.[23] In contrast, Medicaid coverage of mothers and children may differ due to differences in eligibility thresholds.

Medicaid coverage depends on eligibility thresholds that vary by state of residence, year, family size, and a child's age. Mothers and children are eligible if family income is less than the relevant income threshold. Ignoring unearned income, the eligibility rule for mothers is

$$I_{itj}^{M,P} = \mathbf{1}\left\{w_{itj}H_{itj} \leq M_{s(i)t}^{P}\right\}, \tag{5}$$

where $M_{s(i)t}^{P}$ is the eligibility threshold for parental Medicaid according to state of residence s, year, and family size and $w_{itj}H_{itj}$ is monthly earnings.[24] For children, eligibility is determined separately for each age group. Let a index age groups and N_{it}^{a} be the number of children in age group a of mother i at time t. Then, a summary measure for children's Medicaid eligibility is

$$I_{itj}^{M,K} = \frac{1}{\sum_a N_{it}^{a}} \sum_a N_{it}^{a}\mathbf{1}\left\{w_{itj}H_{itj} \leq M_{s(i)t}^{K,a}\right\}, \tag{6}$$

where $M_{s(i)t}^{K,a}$ is the Medicaid eligibility threshold for age group a. Hence $I_{itj}^{M,K} \in [0,1]$.[25]

The above model implies that mothers take up Medicaid coverage for themselves or their children whenever eligible. This seems to be an unrealistic assumption given the evidence for relatively low take-up rates (e.g., Shore-Sheppard, 2008).[26] However, health care providers can sign up eligible patients for Medicaid and have the incentive to do so if the patient cannot pay for treatment herself. Moreover, the goal of this paper is to simulate employment choice under health care reform which includes a health insurance mandate. This mandate is expected to increase take-up of Medicaid.

[23] However, there is empirical evidence that single parents with access to ESHI enroll family members in public health insurance (Vistnes and Schone, 2008). This assumption may be overly simplifying, and I will test its validity in future work.

[24] Medicaid eligibility depends on income, which includes unearned income other than welfare and food stamp payments. However, since I do not observe these income sources in the data, I am forced to make the simplifying assumption that unearned income equals zero.

[25] Therefore, $I_{itj}^{M,K}$ is not an indicator variable but can take on values on the unit interval. It is a summary measure that represents the fraction of children in a family who are eligible for Medicaid. Using this variable implies that mothers only care about the fraction of their children who are covered by health insurance and not about any particular child being covered. By including the fraction of children covered by health insurance in the utility function instead of their number, I can compare single mothers with different numbers of children.

[26] On the other hand, evidence from administrative data shows that take-up rates for Medicaid are higher than usually estimated based on survey data. Card et al. (2004) find that about 15 percent of individuals who are covered by Medicaid according to administrative data do not report coverage in the Survey of Income and Program Participation.

In addition to the utility function and budget constraint, the model specifies equations for wage and out-of-pocket medical expenditure. The wage is determined by the wage equation

$$w_{itj} = \exp\left[w\left(I_{itj}^{S}, Z_{it}^{w}, u_{it}^{w}\right)\right], \tag{7}$$

where Z_{it}^{w} contains worker and labor market characteristics. The error term u_{it}^{w} is the same for jobs with and without ESHI (i.e. it is not indexed by employment alternatives j). In other words, each period, individuals receive one wage shock and wages differ deterministically by whether a job provides health benefits ($I_{itj}^{S} = \{0, 1\}$). This difference in wages reflects the compensating wage differential between jobs with and without ESHI (e.g., Rosen, 1986). If workers derive positive utility from ESHI coverage and firms pass at least part of the cost of ESHI to their employees, we would expect that wages in jobs with ESHI are lower than in jobs without. Formally, $\partial w_{itj}/\partial I_{itj}^{S} < 0$. However, I assume that all jobs without ESHI pay the same wage irrespective of hours worked. That is, the wage in part-time and full-time employment without ESHI is the same.

The out-of-pocket medical expenditure equations for mothers and children are:

$$E_{itj}^{h} = E^{h}\left(I_{itj}^{S}, I_{itj}^{M,h}, Z_{it}^{E,h}, u_{it}^{E,h}\right), h = P, K, \tag{8}$$

where I_{itj}^{S} and $I_{itj}^{M,h}$ are indicators for ESHI and Medicaid coverage, and $Z_{it}^{E,h}$ contains individual characteristics such as medical conditions. The expenditure shocks $u_{it}^{E,h}$ are the same for all alternatives for a given individual and time period. Out-of-pocket medical expenditure can vary across alternatives, however, since Medicaid and ESHI coverage are alternative specific and affect E_{itj}^{h}. Since I allow out-of-pocket medical expenditure to vary with health insurance status, I implicitly allow for ex post moral hazard. That is, having insurance coverage may affect medical expenditure conditional on having a medical condition. I assume that there is no ex ante moral hazard however. Hence, I take medical conditions as exogenous and assume that they do not depend on health insurance status.[27]

[27] If there is ex ante moral hazard, health insurance could affect medical conditions when insured individuals reduce preventive efforts, for example. This assumption is in line with the empirical evidence reviewed by Zweifel and Manning (2000). There is strong evidence for ex post moral hazard while evidence for ex ante moral hazard is limited.

4 Estimation Strategy

The model described in the previous section consists of four equations: the utility function, a wage equation, and two equations for the out-of-pocket medical expenditure of mothers and children. In this section, I describe the two-step estimator that I use to obtain the parameters in these equations. Figure 4 provides a visual guide to the estimation procedure. Choices over labor supply and ESHI depend on the utility arguments consumption, hours, and health insurance coverage, which are represented by the three circles. These arguments depend on a number of auxiliary variables, such as earnings, medical expenditures, and Medicaid eligibility (shown as rectangles). To obtain these auxiliary variables, I estimate a set of regressions shown as boxes with rounded corners.

The estimation proceeds in two steps: First, I estimate the parameters of the wage and expenditure equations to obtain the conditional distributions of these variables. Since earnings and medical expenditure are only observed for the chosen alternative, I draw counterfactuals for the other alternatives from these conditional distributions. Earnings determine Medicaid eligibility and transfers, so these simulations yield all the components that enter the utility arguments.[28] Since employment choice is discrete, I estimate the preference parameters by multinomial logit in the second step. Instead of imposing fixed preference parameters, I allow for both observed and unobserved heterogeneity in preferences.

Other papers also discretize the hours distribution in estimating labor supply models. Zabalza et al. (1980), Fraker and Moffitt (1988), and van Soest (1995) are early examples. Two other studies use a similar estimation method and also consider health insurance, but their focus is different from my paper. Keane and Moffitt (1998) estimate the labor supply effects of welfare programs. They also distinguish between full-time and part-time work and estimate a multinomial logit model with random preference parameters. However, they do not treat employment with ESHI as separate choice. Buchmueller and Valletta (1999) use a discrete choice framework with full-time and part-time work to estimate the effects of ESHI on the labor supply of married women. In contrast to the present paper, they treat the employment choice in a reduced-form manner and do not estimate a wage equation.

[28] Simulation of the utility arguments is necessary since they enter the choice probabilities nonlinearly. In other words, I have to integrate out the wage and expenditures to obtain choice probabilities, and I approximate this integration by drawing from the respective conditional distributions.

4.1 Wage Equation

In this section, I describe how I estimate the wage equation in order to obtain the conditional wage distribution, which I use to simulate earnings. I specify the wage equation (7) as follows:

$$\ln w_{it} = \gamma^S \ln (SC_{it}) \times I^S_{it} + Z^{w\prime}_{it}\gamma^w + a^w_i + u^w_{it}, \tag{9}$$

where w_{it} is the hourly wage and SC_{it} is the hourly ESHI premium paid by the employer of individual i at time t.[29] The ESHI cost variable only enters the wage regression if the individual works full-time with health benefits (i.e., $I^S_{it} = 1$). Hence, the parameter γ^S represents the pass-through of health insurance costs to wages and corresponds to the compensating wage differential between jobs with and without ESHI (see discussion on page 17). Z^w_{it} is a vector of individual and time specific characteristics and includes a quadratic in the mother's age, race, ethnicity, her education, and state unemployment rate and minimum wage. Table **??** lists the independent variables entering this and the other first-step regressions. a^w_i is an unobserved individual effect and u^w_{it} is a normal i.i.d. error term.[30] Since there is a substantial number of non-working single mothers in the sample, I control for selection into the labor force as discussed below.

Using panel data facilitates identification of the parameters of interest, γ^S and γ^w, since differencing out the unobserved individual effects a^w_i accounts for potential correlation between the regressors and individual-specific time-invariant heterogeneity. In particular, I specify a^w_i as a correlated random effect:

$$a^w_i = \bar{Z}^w_i \psi^w + \tilde{a}^w_i,$$

where $\bar{Z}^w_i$ is the vector of within-individual means of the observable characteristics and $\tilde{a}^w_i$ is an i.i.d. error term. However, I also have to assume that the regressors Z^w_{it} are strictly exogenous conditional on the individual effect a^w_i. In other words, they cannot depend on contemporaneous, past, or future wage shocks $u^w_{it'}, \forall t'$. I estimate the model using only two observations from two adjoining years for each single mother so that any dependence of the regressors on past or

[29] SC_{it} is not available in the individual-level data I use and is only measured at the state level. I calculate this variable as the average annual health insurance premium for family insurance paid by employers divided by annual hours worked. Since only individuals who work full-time are eligible for ESHI coverage, I use 40×52 as the number of hours worked per year.

[30] There is no alternative specific subscript j in the wage and medical expenditure regressions since they only use one observation for each individual and time period. However, based on the resulting estimates, I simulate wages and expenditure for all four employment alternatives.

future shocks would have to be in the very short term in order to invalidate the strict exogeneity assumption.

In order to correct for selection bias in estimating equation (9), I use a two-step selection correction approach in the spirit of Heckman (1979). However, I need to account for two features of equation (9) that invalidate the standard approach. First, the wage equation (9) contains unobserved individual effects. Second, in addition to selection into labor force participation (LFP), there is selection into jobs with or without ESHI coverage. In particular, the wage differs between jobs with and without health benefits if $\gamma^S \neq 0$. To account for these complications, I combine the methods of Tunali (1986) and Wooldridge (1995) to develop a selection correction procedure with two selection equations and unobserved individual effects. Details and derivations of this estimation procedure appear in Appendix A.

I specify two selection equations for LFP (L_{it}) and ESHI coverage (I_{it}^S):

$$\begin{aligned} L_{it} &= \mathbf{1}\left\{Z_{it}^{L\prime}\delta^L + a_i^L + u_{it}^L > 0\right\} && (10) \\ I_{it}^S &= \mathbf{1}\left\{Z_{it}^{S\prime}\delta^S + a_i^S + u_{it}^S > 0, L_{it} = 1\right\}, && (11) \end{aligned}$$

where Z_{it}^L and Z_{it}^S are vectors of individual characteristics, a_i^L and a_i^S are individual unobserved effects, and u_{it}^L and u_{it}^S are i.i.d. error terms that have a trivariate normal distribution together with the wage error u_{it}^w.[31] Notice that the ESHI indicator I_{it}^S is only observed if $L_{it} = 1$, i.e. if the individual works in a given period. Z_{it}^L and Z_{it}^S include the following variables that are excluded from Z_{it}^w (see Table 3): state-level Medicaid thresholds (Z_{it}^L and Z_{it}^S), state-level availability and cost of ESHI (Z_{it}^S), and the number of children in different age groups and children's medical conditions (Z_{it}^L).[32]

Given the assumption of joint normality, I estimate the coefficients δ^L and δ^S in equations (10) and (11) using a bivariate probit with incomplete observability separately for each time period.[33] Then I calculate selection correction terms for each time period based on the resulting estimates. These correction terms are the multidimensional equivalent of the inverse Mills ratio. Finally, I add the selection correction terms and interactions with ESHI and time dummies to the wage

[31] For this selection correction procedure, it is not necessary to assume joint normality with the wage shock. However, to obtain individual contributions to the likelihood function when estimating the preference parameters, I need to make a distributional assumption for the wage shock (see equation (22) below).

[32] See Section 5 for a description of these variables.

[33] Bivariate probit with incomplete observability is equivalent to a Heckman selection model with a probit outcome equation, and I estimate it using Stata's heckprob command.

equation:

$$
\begin{aligned}
\ln w_{it} = {} & \gamma^S \ln(SC_{it}) \times I_{it}^S + Z_{it}^w \gamma^w + \bar{Z}_i^w \psi^w + \bar{Z}_i^L \psi^L + \bar{Z}_i^S \psi^S \\
& + \left(\rho_1 \lambda_{it}^{10,L} + \rho_2 \lambda_{it}^{10,S}\right) \times \left(1 - I_{it}^S\right) + \left(\rho_3 \lambda_{it}^{11,L} + \rho_4 \lambda_{it}^{11,S}\right) \times I_{it}^S \\
& + \left(\rho_5 \lambda_{it}^{10,L} + \rho_6 \lambda_{it}^{10,S}\right) \times \left(1 - I_{it}^S\right) \times T_{it}^2 + \left(\rho_7 \lambda_{it}^{11,L} + \rho_8 \lambda_{it}^{11,S}\right) \times I_{it}^S \times T_{it}^2 + \tilde{u}_{it}^w, \qquad (12)
\end{aligned}
$$

where the λ-terms are the selection correction terms, the ρs are coefficients, and T_{it}^2 is an indicator for the second period ($t = 2$).[34] I include the within-individual means $\bar{Z}_i^w$, $\bar{Z}_i^L$, and $\bar{Z}_i^S$ to account for the unobserved effects in the wage, LFP, and ESHI equations.[35] Following Wooldridge (1995) I estimate equation (12) by pooled OLS, which yields consistent estimates of γ^S and γ^w.

The model discussed in Section 3 features a compensating wage differential between jobs with and without ESHI coverage, which is represented by the parameter γ^S in equations (9) and (12). Theoretically, this parameter should be negative since health benefits constitute a part of the overall compensation package, and workers should be willing to accept a lower wage in exchange for ESHI coverage. Empirically, however, there is mixed evidence on the sign and magnitude of γ^S.[36] Using policies mandating the coverage of childbirth and the Massachusetts health care reform, respectively, Gruber (1994) and Kolstad and Kowalski (2011) estimate that firms shift the entire health insurance cost to their workers. Baicker and Chandra (2006) find a pass-through of about 20 percent of the cost using instrumental variables estimation. Panel estimates by Anand (2011) yield a pass-through rate of about 50 percent. Since I lack a plausible strategy to control for unobserved worker heterogeneity and matching between firms and workers, I fix the coefficient γ^S using external estimates.[37] In the results shown in this paper, I set γ^S to -1, which corresponds to a complete pass-through of ESHI costs. As a robustness check, I also show results based on estimating the wage equation with γ^S being unrestricted.

After estimating equation (12) via pooled OLS, I simulate wages for jobs with and without ESHI for each individual and time period. Given the functional form in equation (12) and using

[34] See Appendix A on how the λs are calculated and how the interactions are derived.

[35] This procedure only leads to consistent estimates under additional assumption regarding the conditional expectation of the fixed effects. Again, I describe these assumption in Appendix A.

[36] The older studies reviewed by Currie and Madrian (1999), and Simon (2001) and Levy and Feldman (2001) find a positive relationship between ESHI provision and wages. On the other hand, Miller (2004) estimates a negative relationship.

[37] Moreover, I use the estimated wage parameters to simulate counterfactual wages for workers who are not working. This makes it impossible to control for job-specific characteristics such as occupation.

state-level minimum wages as wage floors, the simulated wages for the r-th simulation draw are

$$\hat{w}_{it}^{0,(r)} = \max\left\{\exp\left(\tilde{Z}_{it}^{w\prime}\hat{\tau}^{w} + \tilde{u}_{it}^{(r)}\right), w_{s(i)t}^{min}\right\}$$

and

$$\hat{w}_{it}^{1,(r)} = \max\left\{\exp\left(\hat{\gamma}^{S}\ln\left(SC_{it}\right) + \tilde{Z}_{it}^{w\prime}\hat{\tau}^{w} + \tilde{u}_{it}^{(r)}\right), w_{s(i)t}^{min}\right\},$$

where $\tilde{Z}_{it}^{w}$ contains all regressors from equation (12) including the selection correction terms but excluding I_{it}^{S}, $\hat{\tau}^{w}$ is a vector of corresponding estimated coefficients, and $\hat{\gamma}^{S}$ is either the restricted or the estimated compensating differential parameter. I draw the wage shock $\tilde{u}_{it}^{(r)}$ from the estimated distribution $\mathcal{N}\left(0, \hat{\sigma}_{w}^{2}\right)$, where $\hat{\sigma}_{w}^{2}$ is the estimated variance of the error term in regression (12).[38] $w_{s(i)t}^{min}$ is the minimum wage in the state $s(i)$ where the individual resides.[39] Finally, I replace simulated wages by the observed wage w_{it} for the chosen alternative so that the simulated wage for employment alternative j becomes

$$\hat{w}_{itj}^{(r)} = \begin{cases} \hat{w}_{it}^{0,(r)} & \text{if } j \neq k \text{ and } j = p, f_0 \\ \hat{w}_{it}^{1,(r)} & \text{if } j \neq k \text{ and } j = f_1 \\ w_{it} & \text{if } j = k \end{cases},$$

where k is the alternative that individual i chooses at time t.

The simulated wage $\hat{w}_{itj}^{(r)}$ and hours worked determine monthly earnings for all employment alternatives. Hours worked $\hat{H}_{itj}$ are either the observed number for the chosen alternative or 20 and 40 for part-time and full-time employment, respectively. Given predicted and observed earnings for all alternatives, I simulate government transfers (denoted by $T\left(\hat{w}_{itj}^{(r)}\hat{H}_{itj}\right)$) and Medicaid eligibility for mothers and children (denoted by $\hat{I}_{itj}^{M,P,(r)}$ and $\hat{I}_{itj}^{M,K,(r)}$, respectively). I calculate transfers as the sum of welfare benefits (TANF), food stamps, and the Earned Income Tax Credit (EITC) and subtracting federal income and payroll taxes.[40]

[38] Note that the wage shocks are identical for both types of jobs.

[39] Note that I include the minimum wage among the regressors in the wage equation (12).

[40] Equations (5) and (6) in Section 3 describe the construction of the Medicaid eligibility variables. Appendix B contains details about these programs and the rules used to calculate transfers given monthly earnings.

4.2 Medical Expenditure Equations

The out-of-pocket medical expenditure regressions for mothers and children correspond to equation (8) in the theoretical model. Out-of-pocket expenditures are a function of health insurance coverage (Medicaid and ESHI) and other individual characteristics. Based on predicted Medicaid coverage, $\hat{I}_{itj}^{M,P}$ and $\hat{I}_{itj}^{M,K}$, and ESHI coverage $I_{itj}^{S}=\mathbf{1}\{j=f_1\}$, I use these estimates to simulate mothers' and children's out-of-pocket medical expenditures under the four employment and health insurance coverage alternatives. Hence, I use variation in Medicaid thresholds across states and time in order to estimate the effect of Medicaid coverage on medical expenditure.

To account for the high fraction of zeros and the skewness in the expenditure distribution, I estimate two-part models for mothers' and children's out-of-pocket expenditure (e.g., Mullahy, 1998). In the first part, I estimate a probit for medical expenditure exceeding zero and in the second part, I use a log-transformation of strictly positive expenditure.

Hence, the two-part model consists of the following two equations:

$$\begin{aligned} \mathbf{1}\left\{E_{it}^{h}>0\right\} &= \mathbf{1}\left\{Z_{it}^{h\prime}\zeta^{h,1}+\zeta^{S,h,1}I_{it}^{S}+a_i^{h,1}+u_{it}^{h,1}>0\right\} && (13)\\ \ln\left(E_{it}^{h}\right)|E_{it}^{h}>0 &= Z_{it}^{h\prime}\zeta^{h,2}+\zeta^{S,h,2}I_{it}^{S}+a_i^{h,2}+u_{it}^{h,2}, h=P,K && (14)\end{aligned}$$

for mothers ($h=P$) and children ($h=K$), where E_{it}^{P} is a mothers' annual out-of-pocket medical expenditure and E_{it}^{K} is the sum of expenditures for her children.[41] Z_{it}^{P} and Z_{it}^{K} contain demographics, the number of medical conditions, and Medicaid eligibility of mothers and children, respectively (see Table 3).[42] Medicaid eligibility is based on simulated earnings ($\hat{I}_{itj}^{M,P,(r)}$ and $\hat{I}_{itj}^{M,K,(r)}$, see above). I_{it}^{S} denotes ESHI coverage and $u_{it}^{h,1}$ and $u_{it}^{h,2}, h=P,K$ are normally distributed time specific expenditure shocks. I specify the individual effects as correlated random effects as follows:

$$a_i^{h,\ell}=\bar{Z}_i^{h\prime}\pi^{h,\ell}+\tilde{a}_i^{h,\ell}, h=P,K,\ell=1,2, \qquad (15)$$

where $\tilde{a}_i^{h,\ell}$ is normally distributed and $\bar{Z}_i^{h}$ is the within-individual mean of the observable vector Z_{it}^{h}.

[41] Out-of-pocket medical expenditures are health care expenditures incurred by the family, i.e. both cost sharing (deductibles and copayments) for insured individuals and medical expenditures paid for uninsured family members, or the cost of medical services not covered by health insurance. They do not include health insurance premiums.

[42] The medical conditions include long-term life threatening conditions, such as cancer, hypertension, and stroke; chronic, manageable conditions such as asthma and back problems; and mental health issues.

There are two issues with these expenditure regressions. First, the same considerations about the necessary strict exogeneity assumption apply as in the wage regression. Second, there is likely to be selection into jobs with ESHI coverage. Since I consider only out-of-pocket expenditure, it is not clear if ESHI status and unobserved determinants of medical expenditure are positively or negatively related, however. Being covered by ESHI may lead to lower out-of-pocket expenditure conditional on observables since the health insurance plan pays for medical care. On the other hand, individuals who are covered by ESHI may have an overall higher need for medical care, so that even their out-of-pocket expenditure is higher. I use the ESHI selection equation (11) from Section 4.1 again to control for selection into ESHI. I obtain predicted ESHI coverage $\hat{I}_{it}^S$ as the marginal probability of having ESHI from the bivariate probit of LFP and ESHI and substitute it for I_{it}^S into equations (13) and (14).

With these assumptions, I write the regressions corresponding to the first part of the two-part model (equation (13)) in terms of the probability of observing positive medical expenditures as follows:

$$\Pr\left(E_{it}^h > 0\right) = \Phi\left(Z_{it}^{h\prime}\zeta^{h,1} + \zeta^{S,h,1}\hat{I}_{it}^S + \bar{Z}_i^{h\prime}\pi^{h,1}\right), h = P, K, \tag{16}$$

where the first two terms follow from equations (13) and (15). Since the composite error term equals $\tilde{u}_{it}^{h,1} = u_{it}^{h,1} + \tilde{a}_i^{h,1}$ and both of these terms are normally distributed, the probability (16) is a normal c.d.f. Therefore, I estimate the coefficients of this probability via probit on the whole sample for both time periods. Accordingly, the second part of the two-part model (equation (14)) becomes

$$\ln\left(E_{it}^h\right)|E_{it}^h > 0 = Z_{it}^{h\prime}\zeta^{h,2} + \zeta^{S,h,2}\hat{I}_{it}^S + \bar{Z}_i^{h\prime}\pi^{h,2} + \tilde{u}_{it}^{h,2}, \tag{17}$$

where $\tilde{u}_{it}^{h,2} = u_{it}^{h,2} + \tilde{a}_i^{h,2}$ is a normally distributed composite error term.

Based on the estimated coefficients in equations (16) and (17) and given the functional form assumptions of the two-part model, I simulate out-of-pocket medical expenditures $\hat{E}_{itj}^{P,(r)}$ and $\hat{E}_{itj}^{K,(r)}$ for all four employment alternatives. The simulated out-of-pocket medical expenditures for mothers and children, respectively, for employment alternatives without ESHI coverage are

$$\hat{E}_{itj}^{h,(r)} = \mathbf{1}\left\{\hat{Z}_{itj}^{h\prime}\hat{\zeta}^{h,1} + \bar{Z}_i^{h\prime}\hat{\pi}^{h,1} + \tilde{u}_{it}^{h,1} > 0\right\} \times \exp\left(\hat{Z}_{itj}^{h\prime}\hat{\zeta}^{h,2} + \bar{Z}_i^{h\prime}\hat{\pi}^{h,2} + \tilde{u}_{it}^{h,2,(r)}\right), h = P, K$$

for $j = n, p, f_0$. Similarly, for full-time work with ESHI coverage ($j = f_1$) the simulated out-of-pocket expenditures are

$$\hat{E}_{itj}^{h,(r)} = \mathbf{1}\left\{\hat{Z}_{itj}^{h\prime}\hat{\zeta}^{h,1} + \hat{\zeta}^{S,h,1}I_{it}^{S} + \bar{Z}_{i}^{h\prime}\hat{\pi}^{h,1} + \tilde{u}_{it}^{h,1} > 0\right\} \times \exp\left(\hat{Z}_{itj}^{h\prime}\hat{\zeta}^{h,2} + \hat{\zeta}^{S,h,2}I_{it}^{S} + \bar{Z}_{i}^{h\prime}\hat{\pi}^{h,2} + \tilde{u}_{it}^{h,2,(r)}\right), h = P, K,$$

where $\tilde{u}_{it}^{h,1,(r)}$ and $\tilde{u}_{it}^{h,2,(r)}$ are draws from $\mathcal{N}\left(0, \hat{\sigma}_{h,1}^2\right)$ and $\mathcal{N}\left(0, \hat{\sigma}_{h,2}^2\right)$, respectively, where $\hat{\sigma}_{h,1}^2$ and $\hat{\sigma}_{h,2}^2$ are the estimated variances of the composite errors $\tilde{u}_{it}^{h,1}$ and $\tilde{u}_{it}^{h,2}$. For the simulations I use the actual ESHI coverage indicator. The vector of alternative-specific characteristics $\hat{Z}_{itj}^{E,h}$ contains simulated Medicaid eligibility, $\hat{I}_{itj}^{M,h,(r)}$, for the corresponding alternative. Finally, I replace predicted expenditures with observed expenditures for the chosen alternative k, hence:

$$E_{itj}^{h,(r)} = \begin{cases} E_{it}^{h} & \text{if } j = k \\ \hat{E}_{itj}^{h,(r)} & \text{if } j \neq k \end{cases}, h = P, K. \tag{18}$$

4.3 Utility Equation

Using the conditional distribution of wage and medical expenditure estimated above, I simulate earnings and expenditures based on simulation draws of wage and expenditure shocks. Having simulated earnings and medical expenditure, all required components are available to obtain the utility arguments consumption (C_{itj}), hours worked (H_{itj}), and health insurance coverage (I_{itj}^{P} for mothers and I_{itj}^{K} for children) for all four alternatives. I specify a quadratic functional form for the utility function that is both flexible and tractable, and includes the squared values of the continuous variables and interactions between all arguments.[43] Consumption and health insurance coverage depend on simulated earnings and out-of-pocket medical expenditure, so I calculate utility for each simulation draw:

$$\begin{aligned} U_{itj}^{(r)} &= \tilde{C}_{itj}^{(r)} + \beta_i^H \tilde{H}_{itj} + \beta_i^P I_{itj}^{P,(r)} + \beta_i^K I_{itj}^{K,(r)} + \alpha^{CC}\left(\tilde{C}_{itj}^{(r)}\right)^2 + \alpha^{HH}\left(\tilde{H}_{itj}\right)^2 \\ &\quad + \alpha^{CH}\tilde{C}_{itj}\tilde{H}_{itj} + \alpha^{CP}\tilde{C}_{itj}^{(r)} I_{itj}^{P,(r)} + \alpha^{CK}\tilde{C}_{itj}^{(r)} I_{itj}^{K,(r)} + \alpha^{HP}\tilde{H}_{itj} I_{itj}^{P,(r)} \\ &\quad + \alpha^{HK}\tilde{H}_{itj} I_{itj}^{K,(r)} + \alpha^{PK} I_{itj}^{P,(r)} I_{itj}^{K,(r)} + \gamma_j^p + \eta_{itj} \\ &= V_{itj}^{(r)} + \eta_{itj}, \end{aligned} \tag{19}$$

[43] This functional form is similar to the one used in Keane and Moffitt (1998).

where η_{itj} is extreme value type I distributed. Marginal utility from consumption is normalized to one, so the random preference parameters $\beta_i = \left(\beta_i^H, \beta_i^P, \beta_i^K\right)'$ and the fixed preference parameters $\alpha = \left(\alpha^{CC}, \alpha^{HH}, \alpha^{CH}, \alpha^{CP}, \alpha^{CK}, \alpha^{HP}, \alpha^{HK}, \alpha^{PK}\right)$ are measured in dollars. The parameter γ_j^p is a utility constant that equals γ if $j = p$ and zero otherwise. That is, utility shifts by a fixed amount in the part-time alternative in order to better fit the choice proportions in the data (van Soest, 1995).

Given the budget constraint (3) and the scale assumption (2), I calculate real per capita monthly consumption in \$1,000 as

$$\tilde{C}_{itj}^{(r)} = \frac{1}{1000 \times \left(1 + \sqrt{NK_{it}}\right) \times CPI_t} \left[\frac{12}{52} w_{itj}^{(r)} H_{itj} + T\left(\frac{12}{52} w_{itj}^{(r)} H_{itj}\right) - \frac{prem_{itj} + E_{itj}^{P,(r)} + E_{itj}^{K,(r)}}{12}\right], \quad (20)$$

where NK_{it} is number of children, CPI_t is the price index used to obtain real values, and $prem_{itj}$ is the part of the annual health insurance premium paid by the individual. In the estimation, a premium is only required for ESHI. When I simulate employment choice under health care reform, however, individuals also pay premiums for subsidized health insurance according to the schedule in Table 1. I normalize hours worked as $\tilde{H}_{itj} = H_{itj}/40$, where H_{itj} is observed hours worked, or 20 or 40 depending on the employment alternative. $I_{itj}^{P,(r)}$ and $I_{itj}^{K,(r)}$ are calculated according to equations (4), (5), and (6) in Section 3 using simulated earnings in the Medicaid eligibility rules.

The preference parameters β_i are correlated coefficients that depend on observables and unobservables as follows:

$$\beta_i \sim \mathcal{N}\left(Z_i^u \delta, \Sigma\right), \quad (21)$$

where Z_i^u is vector of observables and δ is a matrix of coefficients. Σ is an unrestricted variance-covariance matrix. Table 2 shows the variables that enter Z_i^u and for which components of the preference vector β_i they matter. Not all elements of Z_i^u affect all three elements of β_i. I account for these exclusion restrictions by setting the corresponding elements of δ to zero. Note that preference parameters are individual specific and do not change over time. The preference parameters on the second order terms, α, and the part-time utility constant γ are fixed over individuals.

	β_i		
Z_i^u	hours	HI, mother	HI, children
mother's age	X	X	
black, Hispanic	X	X	X
number of children under 4	X		
number of mother's conditions		X	
age of youngest child			X
number of children's conditions			X

Table 2: **Individual Characteristics Affecting Preference Parameters**

4.4 Multinomial Logit Estimation

Let $X_{itj}^{u,(r)} = \left(\tilde{C}_{itj}^{(r)}, \tilde{H}_{itj}, I_{itj}^{P,(r)}, I_{itj}^{K,(r)}\right)$ denote the vector of utility function arguments for individual i, time t, and alternative j in simulation draw r. Given the distributional assumption about the error term η_{itj} in equation (19), the probability that individual i chooses alternative j at time t has the multinomial logit form conditional on the preference parameters β_i and utility function arguments $X_{itj}^{u,(r)}$ for all alternatives:

$$p_{itj}^{(r)}\left(\beta_i\right) \equiv \Pr\left(d_{itj} = 1 | \beta_i, \alpha, \gamma, \left\{X_{itk}^{u,(r)}\right\}_{k=n,p,f_0,f_1}\right) = \frac{\exp\left[V_{itj}^{(r)}\left(\beta_i\right)\right]}{\sum_{k=n,p,f_0,f_1} \exp\left[V_{itk}^{(r)}\left(\beta_i\right)\right]},$$

where d_{itj} is an indicator for the chosen alternative and $V_{itj}^{(r)}$ is defined in equation (19). Hence the unconditional choice probability for individual i over both time periods averaging over simulation draws $r = 1, \ldots, R$ is

$$\pi\left(\delta, \Sigma; \left\{X_{itk}^{u,(r)}\right\}_{k=n,p,f_0,f_1}^{t=1,2}, Z_i^u\right) = \int_{\beta_i} \prod_{t=1}^{2} \prod_{j=n,p,f_0,f_1} \left[\frac{1}{R} \sum_{r=1}^{R} p_{itj}^{(r)}\left(\beta_i\right)\right]^{d_{itj}} d\mathbf{\Phi}\left(\beta_i | Z_i^u \delta, \Sigma\right), \quad (22)$$

where $\mathbf{\Phi}\left(\cdot | Z_i^u \delta, \Sigma\right)$ is the multivariate normal distribution with mean $Z_i^u \delta$ and variance Σ.

Hence, the log-likelihood function is

$$LL\left(\theta\right) = \sum_{i=1}^{N} \ln \pi\left(\theta; \left\{X_{itk}^{u}\right\}_{k=n,p,f_0,f_1}^{t=1,2}, Z_i^u\right).$$

Since the log-likelihood function involves an integral over a three-dimensional normal distribution, no analytical expression is available. Instead, I simulate the log-likelihood function as follows:

$$SLL(\theta) = \sum_{i=1}^{N} \ln \left\{ \frac{1}{R'} \sum_{r'=1}^{R'} \prod_{t=1}^{2} \prod_{j=n,p,f_0,f_1} \left[\frac{1}{R} \sum_{r=1}^{R} p_{itj}^{(r)} \left(\beta_i^{(r')} \right) \right]^{d_{itj}} \right\} \tag{23}$$

where $\beta_i^{(r')}$ is the r'th draw from the multivariate distribution $\mathbf{\Phi}(\cdot|Z_i^u\delta, \Sigma)$ and the choice probabilities based on R' such draws are averaged to obtain the likelihood contribution of each individual (Train, 2009).[44] The coefficients to be estimated are $\theta = (\delta, \Sigma, \alpha, \gamma)$.

Then, the Maximum Simulated Likelihood estimation algorithm proceeds as follows:

1. Find starting values $\hat{\theta}^{(0)} = \left(\hat{\delta}^{(0)}, \hat{\Sigma}^{(0)}, \hat{\alpha}^{(0)}, \hat{\gamma}^{(0)}\right)$ using multinomial logit with fixed parameters for $\hat{\delta}^{(0)}$ and setting the diagonal elements of $\hat{\Sigma}^{(0)}$ to one and its off-diagonal elements to zero.

2. Draw from $\mathbf{\Phi}\left(\cdot|Z_i^u\hat{\delta}^{(0)}, \hat{\Sigma}^{(0)}\right)$ R' times for each i and calculate the SLL according to equation (23).[45]

3. Maximize the SLL with respect to θ and obtain $\hat{\theta}^{(1)}$.

4. Iterate steps 2. and 3. until convergence.

I obtain the simulation draws at iteration (s) according to Train (2009, p. 208) as

$$\beta_i^{(r')} = Z_i^u\hat{\delta}^{(s)} + \hat{L}^{(s)}\nu_i^{(r')},$$

where $\hat{L}^{(s)}$ is the lower-triangular square matrix obtained from the Cholesky decomposition of $\hat{\Sigma}^{(s)} = \hat{L}^{(s)}\hat{L}^{(s)\prime}$, and $\nu_i^{(r')}$ is a vector drawn from the three-dimensional standard normal distribution. Instead of drawing pseudo-random numbers for $\nu_{it}^{(r')}$, I follow Bhat's (2001) suggestion to use quasi-random numbers, in particular Halton sequences.[46] These sequences provide quasi-random

[44] I assume that the preference shocks are uncorrelated with the wage and expenditure shocks, so that the simulation draws are separate from the multivariate normal distribution of β_i and three additional error terms for the wage and the expenditure equations (which themselves are uncorrelated with each other).

[45] I keep the R draws for the wage and expenditure simulations and the R' draws for the preference parameters constant so that the choice probabilities $p_{itj}^{(r)}\left(\beta_i^{(r')}\right)$ only change through the distribution parameters at iteration s, $\hat{\delta}^{(s)}$ and $\hat{\Sigma}^{(s)}$.

[46] A Halton sequence results from dividing the unit interval by prime numbers. For example, for the prime 3, the first two elements of the sequence are 1/3 and 2/3. The resulting three intervals are further divided and yield 1/9, 2/9, 4/9, 5/9, 7/9, and 8/9 and so on. This sequence is not random, but pseudo-random numbers are not truly

draws from the uniform distribution, which are then transformed using the inverse of the standard normal density function to obtain the standard normally distributed $\nu_i^{(r')}$.[47] In practice, I set $R = R' = 100$.

Since the multinomial logit regression in the second step of my estimation procedure uses simulated regressors from the first step, conventional standard errors are incorrect. To obtain correct standard errors, I use a nonparametric block bootstrap. For each bootstrapped sample, I carry out the two-step estimation procedure described above and save the estimated parameter vector $\hat{\theta}$. Then I obtain standard errors as the square roots of the diagonal elements of the variance matrix of the $\hat{\theta}$-estimates. Since the exogenous variation is at the state-year level, drawing bootstrap samples at the individual level would lead to inconsistent standard errors. For correct inference, I follow Cameron et al. (2008) and draw clustered bootstrap samples at the state level (block bootstrap). This procedure accounts for dependence between individuals and across time within states.

4.5 Identification

This section does not contain a formal identification proof, but I provide an intuitive argument that the parameter vector θ is identified. Identification comes from both quasi-experimental variation in Medicaid eligibility rules and the structure imposed on the estimation method. In addition, I exploit within-individual variation.

Medicaid policies and other program rules that differ by state (such as welfare) are treated as exogenous. Although this is not a perfect experiment, there are many studies that treat between-state variation as exogenous. Moreover, I use variation in these policies over time.[48] This exogeneity assumption may be violated if individuals choose their location based on Medicaid generosity. In the context of welfare, Kennan and Walker (2010) show that individuals do not migrate to a different state to take advantage of higher welfare payments. Another concern is that single mothers may base their marriage and fertility decisions on Medicaid rules, which vary by family size. This

random either, so that a simulation estimator has the same properties using either method for drawing "random" numbers. Train (1999) shows that much fewer (e.g., 100 instead of 1000) simulation draws are necessary when using a Halton sequence versus pseudo-random numbers to obtain the same variance of the simulation estimator because Halton sequences cover the unit interval more evenly than pseudo-random numbers.

[47] In order to ensure proper values for the estimated variance-covariance matrix $\hat{\Sigma}^{(s)}$ at each iteration, i.e. positive values for diagonal elements and correlations between -1 and 1 for off-diagonal elements, I transform the estimated values using the formulae suggested by Haan and Uhlendorff (2006).

[48] I also use the variation in Medicaid thresholds across states and over time in reduced-form regressions of employment choice on Medicaid eligibility (see Section 6.1).

would also contradict Medicaid rules being exogenous. Bitler et al. (2004) find that welfare reform in the 1990s reduced the marriage rate, but this result is not very robust. Although there is no direct evidence on the relationship between Medicaid and location choice, fertility, and marriage, respectively, the exogeneity assumption is plausible in light of this evidence.

Identification is also aided by within-individual variation. Since I use panel data from the Medical Expenditure Panel Survey with two observations for each single mother, there are individuals who experience changes in Medicaid and other policies while they are in the sample.[49] In practice, this source of identification is implemented by using correlated random effects in the wage and expenditure regressions in the first step, and time invariant preference parameters in the multinomial logit estimation in the second step.

For the wage and medical expenditure regressions, I assume strict exogeneity of the independent variables as discussed above. This also includes the medical conditions of mothers and children, which enter the wage, LFP, and ESHI equations (9), (10), and (11) and the medical expenditure equations (13) and (14). Hence, for identification, I need to assume that past and future medical conditions do not affect wage or medical expenditure shocks.

In addition to exploiting exogenous variation in Medicaid policies, I also impose structure on the estimation that allows me to identify the preference parameters. In particular, I postulate a quadratic utility function and assume that the random preference parameters have a joint normal distribution (see equations (19) and (21)). Walker et al. (2007) show that the mean and variance parameters in a multinomial logit model with random coefficients are identified for both continuous and categorical independent variables. Therefore, identification does not rely solely on exogenous variation in policy parameters and changes in medical condition or on the imposed structure, but rather on the combination of the two.

5 Data and Summary Statistics

The Medical Expenditure Panel Survey (MEPS) is a large-scale longitudinal and nationally representative survey of households, their medical providers, and employers carried out by the Agency of Healthcare Research and Quality (AHRQ).[50] It collects extensive information on the use of health

[49] See Figure 2. For example, single mothers who are observed in 1997 and 1998 and reside in the District of Columbia experience a fourfold increase in the Medicaid eligibility threshold.

[50] Data files and documentation are available from http://www.meps.ahrq.gov/mepsweb/data_stats/download_data_files.jsp.

care, associated expenditures, health insurance coverage, and medical conditions. In addition, it contains information of individuals' labor market outcomes and socio-demographic variables. The MEPS interviews each household five times over a period of 2.5 years. It is a rotating panel and has drawn a new sample every year since its start in 1996. Data for 12 completed panels are available to date (from the 1996 panel to the 2007 panel).

Since the public use version of the MEPS does not include geographic information, and estimating the effect of Medicaid policies on labor supply requires knowledge of individuals' state of residence, this paper uses restricted MEPS data that is not publicly available.[51] State identifiers are encrypted in the restricted use version, but households are matched to state-level policy variables such as Medicaid eligibility thresholds and welfare rules.

Although the MEPS interviews each household five times within two years, some variables are measured at the annual level. In particular, the MEPS only contains annual medical expenditure variables. Therefore, I use data from one interview round for each year so that there are two observations for each household. I choose rounds 2 and 4 for variables that are measured at the round-level, i.e. all labor market variables. Rounds 2 and 4 both take place in the middle of the respective year so that no seasonal adjustments are necessary. To generate the estimation sample, I pool data from all panels.

To obtain a sample of single mothers, I select female household heads who are not married and have at least one child under the age of 18. The mothers' age is restricted to the range 18 to 55. From this sample, I select women who have at most five children. This is necessary because Medicaid eligibility thresholds vary by family size and I only have access to these thresholds for a maximum of six family members. Single mothers with more than five children constitute less than one percent of the initial sample. Moreover, I construct a balanced panel by dropping individuals who are only observed for one year. I also drop single mothers who move between states between the first and second year in the sample.[52] Finally, I drop individuals who reside in states with fewer than 30 observations over the whole sample period, which leaves single mothers from 37 states in the estimation sample. Overall, these restrictions yield an estimation sample consisting of 5,139 single mothers, each of them observed for two time periods.

[51] I carried out the empirical analysis at the New York Census Research Data Center of the U.S. Census Bureau.

[52] Medicaid rules are unlikely to play an important role in migration between states. Kennan and Walker (2010) find that welfare rules have only a small impact on migration among young women. Therefore, it is unlikely that differences in Medicaid rules significantly affect mobility between states.

Table 4 displays summary statistics for the individual-year-level variables used in the estimation broken down by observed employment status (not working, part-time, full-time without ESHI, and full-time with ESHI, where part-time employment as defined as working less than 35 hours per week). The first two rows show frequencies and percentages for each employment category. About one third of year-level observations fall into the non-working and full-time work with ESHI categories, respectively, about one fifth of the sample work full-time without ESHI, and the remainder is in part-time work.

Characteristics of single mothers vary between employment alternatives. Women with full-time work and ESHI coverage are older, less likely to be Hispanic, and have more education on average. Their hourly wage is higher than that of single mothers in jobs without ESHI coverage. This seems to contradict the compensating differentials argument made above. However, this is not surprising since the table shows unconditional averages. Single mothers who are not employed not only have more children but also younger children than those working. They are also less healthy on average, measured by the fraction that has any medical conditions and by the average number of conditions. Among working mothers, those with ESHI coverage have slightly more medical conditions. The children of non-working mothers are also less healthy on average. Out-of-pocket medical expenditure for both mothers and children are highest among women with ESHI coverage. Medicaid is an important source of health insurance coverage for single parents and their children. Seventy percent of single mothers who do not work and 85 percent of their children are covered by Medicaid. Over 40 percent of women working part time or full time without ESHI and about 70 percent of their children are covered by Medicaid. Overall, this sample of single mothers is relatively poor. Even among women working full-time with ESHI, average income is only 260 percent of the FPL.

Table 5 lists the reasons why single mothers are not employed. The table shows that the majority of single mothers who do not work are not in the labor force. Only 18 percent of non-working women indicate that they could not find work (are unemployed) whereas the rest give some reason implying that they are not looking for employment (i.e. they are not in the labor force). The most widely given reasons are illness and taking care of family. Since most women who are not employed are not currently looking for employment, I do not distinguish between unemployment and not being in the labor force.

Besides individual and family level variables, I merge a number of state-level variables to the MEPS.[53] Table 6 displays summary statistics of these variables. I obtain these statistics from the sample of single mothers, so they are weighted by the number of observations in each year-state cell. According to these weighted means, about 56 percent of firms offer ESHI, and employers pay $3.11 for ESHI per hour. The employee part of the ESHI premium amounts to about $2,200 per year for family coverage. The average threshold for parental Medicaid is about $1,000 per month. This value accounts for the family sizes observed in the sample. For infants, the Medicaid eligibility thresholds is over $2,300 per month. This number decreases to about $1,500 for older children. Using the Medicaid threshold under health care reform with the actual FPL from 1996 to 2008 yields an average eligibility threshold of $1,700, which is significantly higher than under current rules.[54]

6 Estimation Results

In this section, I first show reduced-form evidence on the employment effects of Medicaid expansions. Then I discuss the results for the two-step estimator described in Section 4.

6.1 Reduced-Form Results

When estimating the effect of Medicaid policies on health or labor market outcomes, using individual Medicaid eligibility as an independent variable leads to biased estimates. Actual eligibility is endogenous Medicaid eligibility depends on income, which may be correlated with the unobserved component of the outcome variable. To avoid this problem, Currie and Gruber (1996) propose a simulated eligibility measure. They draw a national sample of women for different demographic cells and calculate the fraction eligible for Medicaid under every state's eligibility rules for each of the cells. Hence, variation in this eligibility variable comes from state policies and not from individual characteristics. Then they instrument individual eligibility with this simulated eligibility measure.

I follow Currie and Gruber's (1996) procedure and divide the MEPS sample of single mothers into 30 demographic cells based on age, race/ethnicity, and education. Then I draw 300 individuals

[53] See Appendix B for details and sources.

[54] I calculate the Medicaid threshold under PPACA using the FPL that was in effect in the years when the respective individual was part of the sample. Hence, these thresholds are calculated as if PPACA had been in effect during the sample period, 1996 to 2008.

from the sample of the pooled 1996 to 2007 MEPS data for each cell. Table 7 shows the simulated fractions of mothers and children eligible for Medicaid over states and years for each demographic cell. These statistics show that younger, minority, and lower educated single mothers and their children are more likely to be eligible for Medicaid. In addition, I provide average fractions eligible for parental and children's Medicaid over states and demographic cells for each year in Table 8. There is a substantial increase in eligibility over time, in particular between 1996 and 2000, reflecting the welfare reforms in 1996.

Tables 9a and 9b show the regression results from linear probability models for each of the four employment choices, including only simulated parental Medicaid eligibility and both parental and children's Medicaid eligibility, respectively.[55] Instrumenting individual Medicaid eligibility with the simulated eligibility measures does not lead to consistent estimates since the relationship between employment choice and Medicaid choice is necessarily nonlinear because of the Medicaid eligibility rules. I avoid this problem by using the simulated eligibility measure as a proxy instead of as an instrument (see Dave et al., 2011).

Parental Medicaid eligibility increases the likelihood of not working and reduces full-time work with ESHI (Table 9a). Adding simulated eligibility for children's Medicaid, makes the effects of parental Medicaid insignificant (Table 9b). Children's Medicaid eligibility decreases the odds of working full-time with ESHI and makes full-time work without ESHI more likely. These results suggest that Medicaid expansions have two main effects on the employment choice of single mothers: first, they lead to work disincentives, consistent with Dave et al.'s (2011) findings. Second, there is substantial crowding-out of ESHI. This finding is also consistent with the literature (Cutler and Gruber, 1996). Hence, expanding Medicaid eligibility affects single mothers' work incentives at both ends of the labor supply distribution. However, these results do not capture heterogeneous effects. To account for heterogeneity and to allow for the different mechanisms in how Medicaid changes work incentives, I estimate a structural model of labor supply with health insurance coverage.

[55] In addition to simulated Medicaid eligibility, these regressions include individual characteristics and state-level variables describing the availability and cost of ESHI and labor market conditions, as well as state and year fixed effects.

6.2 Structural Estimation Results

In this subsection, I present the estimation results for the regressions in the two-step estimator described in Section 4: the wage and expenditure regression for the first step and the multinomial logit for the second step (see Figure 4). I also discuss summary statistics for the simulated variables, such as earnings, Medicaid eligibility, and medical expenditure, that are based on these estimates.

Table 10 shows the estimated coefficients for the wage equation, which include the within individuals means of the time variant regressors in the wage, LFP, and ESHI equations, and selection correction terms that are derived from the estimates of the bivariate probit of LFP and ESHI.[56,57] Since I assume complete pass-through of employers' ESHI cost to wage, the coefficient on the log of hourly ESHI cost is restricted to -1. Single mothers' productivity is negatively related to having any medical conditions. Medicaid eligibility thresholds do not affect wages, which suggest that local labor market conditions and states' Medicaid policies are unrelated. The large and mostly significant coefficients on the selection correction terms (λs) indicate that there is considerable selection into LFP and jobs with ESHI, and it is therefore necessary to control for these variables in the wage equation.

Based on the estimated conditional wage distribution for jobs with and without ESHI, I simulate hourly wages and monthly earnings for the three work alternatives. Their means and standard deviations are shown in panel (a) of Table 11. Estimating a wage equation with selection correction allows me to simulate wages and earnings for all individuals in the sample, including those who are observed not to work. Despite imposing a compensating wage differential, wages are higher in jobs with ESHI because the selection correction terms differ by ESHI status. The average hourly wage is \$9 for jobs without ESHI and \$12.70 for jobs with ESHI. Average earnings are about \$800, \$1,600, and \$2,200 for part-time and full-time jobs without ESHI and full-time jobs with ESHI, respectively.

Monthly earnings determine government transfers and Medicaid eligibility. Transfers are highest in the non-work alternative, at about \$750, since single mothers receive welfare and food stamp payments when not working.[58] Even for full-time jobs, transfers are positive on average due to the

[56]Since I include within-individual means of time variant variables, the coefficients on the levels of these variables represent the effect of a deviation from the within-individual means.

[57]The results for the bivariate probit for the wage selection correction are shown in Table A1 and discussed in Appendix A.

[58]Transfers are calculated as the sum of welfare, food stamps, and taxes (federal income tax, payroll taxes, and the Earned Income Tax Credit) based on the policy rules for described in Appendix B.

Earned Income Tax Credit. Panel (b) of Table 11 contains average health insurance coverage under current Medicaid rules. Coverage comes from Medicaid (for alternatives non-work, part-time, and full-time without ESHI) if simulated monthly earnings are below the relevant threshold, or from ESHI. All single mothers and their children are eligible for Medicaid if they do not work, and the fraction covered by health insurance when working full-time with ESHI is one by definition. Large fractions of single mothers are eligible for Medicaid when holding part-time or even full-time jobs. Eighty-six percent of single mothers are eligible when working part-time and 60 percent are eligible when working full-time. For children's Medicaid, 97 and 75 percent are eligible, respectively.[59]

Table 12 contains the estimates from two-part models of mothers' and children's out-of-pocket medical expenditure. Controlling for demographics and medical conditions, ESHI coverage leads to higher and Medicaid eligibility leads to lower out-of-pocket expenditure.[60] These estimates point to higher cost sharing under ESHI. I cannot rule out, however, that higher demand for health care affects individuals' decisions to obtain ESHI coverage, thereby biasing these estimates. For mothers, the number of medical conditions increases both the probability of having positive expenditure and raises spending. For children, medical conditions are not as strongly associated with medical expenditure.

Using the functional-form assumption of the two-part model and the estimated coefficients, I obtain the conditional distributions of out-of-pocket medical expenditure for mothers and children. Summary statistics for simulated expenditure under current Medicaid rules are shown in panel (b) of Table 11. Based on simulated earnings, transfers, and medical expenditure, I calculate monthly per capita consumption in \$1,000 in 1996 terms for all alternatives according to equation (20). This completes the first step of the estimation procedure, which yields simulated values for the arguments of the utility function (consumption, hours worked, and health insurance coverage) under current Medicaid policies.

In the second step of the two-step estimation procedure, I estimate the preference parameters of the empirical utility function in equation (19) via multinomial logit with correlated random parameters (also known as mixed logit in the literature). The top panel of Table 13 contains the estimated mean and variance-covariance coefficients of the preference parameter distribution, i.e. the matrices δ and Σ in equation (21). The estimates show that women with young children

[59]These fractions are higher than those reported in Table 4 since the latter are self-reported Medicaid coverage while the averages in Table 11 are based on eligibility and assume full take-up.

[60]I use the predicted marginal probability of being covered by ESHI from the bivariate probit for LFP and ESHI instead of actual ESHI coverage (see Section 4.2).

dislike working more, and having medical conditions increases the marginal utility of health insurance coverage for mothers. Children's medical conditions do not affect mothers' preferences for children's health insurance coverage, however. The estimated variance-covariance matrix of the unobserved preference components implies that single mothers who like working more also have a higher preference for health insurance coverage for themselves. The unobserved components of the preferences for own and children's health insurance are negatively correlated. The estimated fixed preference parameters are shown in panel of Table 13. The utility constant for part-time work is estimated to be positive, which implies that single mothers prefer part-time work over not working and working full-time, conditional on the other arguments of the utility function.

Figure 5a visualizes the estimated distributions of the three random preference parameters as kernel density plots. As shown in Table 13, there is heterogeneity in preferences. Since I assume a normal distribution, the preference parameters are not restricted to be negative or positive. For example, Figure 5b shows that the distribution of the hours preference parameter is shifted to the left for mothers with young children. These women dislike working more since they spend more time on child care. Figures 5c and 5d plot the distributions of preference parameters for mother's and children's health insurance coverage by whether or not the mother or her children have any medical conditions, respectively. The distributions for mothers and children with conditions are shifted to the right, implying that those with worse health status value health insurance more.

Since the coefficients in Table 13 are not intuitively interpretable, I also report average marginal effects of the individual characteristics on the probability of choosing each of the four employment alternatives in Table 14.[61] Single mothers with a child under the age of four are eight percent more likely not to work, a little more likely to work part-time, and four to five percent less likely to work full-time. Moreover, the more medical conditions a women has, the more likely she is to choose the non-work and full-time work with ESHI alternatives, which guarantee health insurance coverage. For each additional condition, the choice probabilities increase by 0.4 percent. This result implies that less healthy individuals are constraint in their employment decisions because of health insurance availability. If health insurance were more easily available—such as under health care reform—women who are afraid of losing Medicaid eligibility when working might enter the

[61] I obtain the average marginal effects by first calculating the marginal effect as the difference in predicted probabilities of choosing each employment alternative. Since the individual characteristics are discrete variables, I calculate differences in predicted probabilities based on a discrete change in the independent variables instead of approximating an infinitesimal change. Then I average these marginal effects over all individuals, time periods, and Halton simulation draws.

labor force. On the other hand, individuals who work full-time in order to obtain ESHI could earn a higher wage in a job that does not provide ESHI, but receive subsidized health insurance. These incentives are stronger for less healthy women.

7 Policy Simulation

In this section, I simulate employment choice under health care reform using the preference parameter estimates from the previous section. Before I present the simulation results, I derive theoretical predictions for labor supply and take-up of ESHI in response to health care reform based on the framework discussed in Section 3.

7.1 Predictions for Labor Supply and Take-Up of ESHI

A simplified budget constraint for single mothers who may be eligible for Medicaid and can obtain ESHI in full-time jobs is shown in Figure 6a. Under current policies, mothers are eligible for Medicaid in the range AB. Medicaid increases disposable income by the amount BC since it covers most expenditures for health care. For simplicity, I assume that single mothers are not eligible for Medicaid when working.[62] The segment CH corresponds to part-time work where no health insurance coverage is available under current policies. When a mother works full-time without ESHI, her budget constraint continues on the segment HK. When she works in a job with health benefits, the relevant segment is GL. This segment is less steep than HK because of the compensating wage differential, and shifted up since ESHI coverage increases disposable income. The value of ESHI is given by GH, which is less than the value of Medicaid due to the lower cost-sharing under ESHI.

Health care reform changes the budget set in two ways.[63] First, for a given wage, it increases the range of hours in which individuals are eligible for Medicaid up to point D (shown in Figure 6a). Second, it introduces health insurance subsidies in the range EJ. While Medicaid remains free, the implicit wage of workers who are covered by subsidized health insurance is lower, since subsidies decrease as earnings grow. Hence, segment EJ has lower slope than CH (see Figure 6b).[64]

[62]Single mothers may not be able to find a job that allows them to work the small number of hours that would be required for Medicaid eligibility in states with low eligibility thresholds.

[63]Health care reform also includes other provisions such as employer mandates which may affect employment, but since I only consider labor supply responses in this paper, I abstract from these policy changes here.

[64]The budget constraint in Figure 6b is slightly simplified since the segment EJ, on which a single mother is eligible for health insurance subsidies has several kinks (see Table 1).

The theoretical effects of expanding Medicaid without introducing health insurance subsidies are ambiguous.[65] Individuals who do not obtain ESHI when working full-time are subject to budget constraint ADFK while those with ESHI coverage make decisions based on budget constraint ADFHGL (see Figure 6a). Single mothers who do not work prior to the reform because they are afraid of losing Medicaid eligibility may enter the labor force and receive Medicaid coverage while working part time. For these individuals, the higher payoff from working expands their labor supply. On the other hand, increasing Medicaid eligibility also raises disposable income in the range BD, which leads to higher demand for leisure. If this income effect outweighs the reduced work disincentive (or substitution effect) labor supply decreases. Moreover, the Medicaid "notch," i.e. the sharp drop in eligibility, moves from point B to D so that individuals located above, but close to, point F on the budget line have a lower incentive to work. They may reduce their labor supply to obtain Medicaid coverage.

In addition, individuals who work full-time with ESHI coverage may reduce their labor supply to become eligible for Medicaid. As depicted in Figure 6a, the consumption level when working part-time with Medicaid may be about as high as when working full-time with ESHI because of the higher cost-sharing of Medicaid and the compensating wage differential. Therefore, expanding Medicaid can lead to crowding-out of ESHI in addition to reducing labor supply.[66] Finally, individuals who work full-time without ESHI are unlikely to change their labor supply. They reveal their preference for consumption over health insurance and leisure. Hence, giving them the option to obtain health insurance coverage at lower earnings does not make these workers change their employment choice.

Combining Medicaid expansions and health insurance subsidies makes it more likely for single mothers to increase their labor supply. As Figure 6b shows, the Medicaid "notch" DF almost disappears. Since individuals who become ineligible for Medicaid pay at most two percent of their income for subsidized health insurance, the discontinuity in the budget line is reduced to DE. Overall, health insurance subsidies increase the payoff from working for single mothers who value health insurance highly. Hence, these individuals are expected to increase their labor supply and switch to part-time or full-time work without ESHI. On the other hand, for individuals who do

[65] Although health care reform combines Medicaid expansions and health insurance subsidies, it is important to analyze these policy changes separately. This allows me to infer which part of the reform affects employment and whether effects of different reform components might go in opposite directions.

[66] To simplify the presentation, I assume that working full-time makes single mothers ineligible for Medicaid under the expansion. There are workers with low wages, however, who may be eligible for Medicaid when working full-time. These individuals may drop ESHI coverage without reducing their labor supply.

not value health insurance coverage, the subsidies imply work disincentives since they include an implicit marginal tax on working. If there are enough single mothers who value health insurance, however, expanding Medicaid and introducing subsidized health insurance is expected to increase labor supply overall.

The eligibility threshold for health insurance subsidies at 400 percent of the FPL induces a potential work disincentive since individuals lose the benefit if their income exceeds this level. However, there are two reasons, why I do not expect this effect to be important in this sample of single mothers. First, at 400 percent of the FPL, individuals pay up to 9.5 percent of their income, which is not much different from the average cost of ESHI.[67] Hence, losing this benefit does not have the same effect as losing free health insurance coverage through Medicaid. Second, most single mothers in this sample earn less than the 400 percent threshold. As the summary statistics in Table 4 show, even in the alternative full-time work with ESHI, average income is only about 260 percent of the FPL. Therefore, the work incentives of health care reform are likely to prevail.

In addition, health care reform can lead to lower take-up of ESHI. Full-time work with ESHI is dominated by working full-time without ESHI but with subsidized health insurance since disposable income is always higher on segment EJ than on segment GL. Moreover, depending on the size of the compensating differential, the wage for full-time jobs with ESHI may be lower than the full-time wage without ESHI net of health insurance costs. Hence, health care reform is predicted to lead to crowding-out of ESHI.

So far, I have only considered the labor supply effects of Medicaid expansions and health insurance subsidies that operate through changes in hours worked and disposable income. In my model, however, I include health insurance coverage in the utility function. To the extent that health insurance coverage affects the marginal utility of consumption and leisure, changes in health insurance coverage also influence labor supply through this channel.[68] For example, if better health due to increased coverage raises the marginal utility from consumption more than the marginal utility from leisure, expanding Medicaid and introducing subsidies leads to a larger increase in labor supply. Single mothers who have a high valuation of health insurance coverage because of their own or their children's medical conditions are especially expected to change their behavior

[67] According to MEPS data, average ESHI cost for family plans amounts to 17 percent of family income. Since employers cover a part of this cost, individuals who become ineligible for subsidized health insurance may pay not much more than 9.5 percent of their income for ESHI.

[68] Finkelstein et al. (2008) provide evidence on the positive relationship between health status and marginal utility of consumption, for example.

more when health care reform relaxes the current restrictions on employment and health insurance availability.

7.2 Simulation Results

In this section, I use the estimates from Section 6.2 to simulate single mothers' employment choices under health care reform. I consider two provisions of PPACA: Medicaid expansions and health insurance subsidies. To assess whether these two provisions have a differential impact on labor supply, I simulate employment choices separately under Medicaid expansions only and under both provisions.[69]

To obtain simulated utility for all employment alternatives, I simulate the arguments of the utility function using the estimates from the first-step regressions. Summary statistics for simulated health insurance coverage, medical expenditure, and consumption are show in panels (c) and (d) of Table 11. Under Medicaid expansions only (panel (c)), health insurance coverage increases substantially. When working part-time, 99 percent of single mothers and their children are covered by Medicaid and when working full-time, 83 percent of mothers and 86 percent of children are covered.[70,71] Average consumption does not change significantly relative to current Medicaid rules.

Under both PPACA provisions (panel (d)), health insurance coverage is virtually universal for single mothers and their children in all four employment alternatives. These statistics show that health care reform will lead to a substantial increase in health insurance coverage for single parent households.[72] Average simulated consumption is lower under combined Medicaid expansions and health insurance subsidies when working part-time and full-time, since cost-sharing under subsidized health insurance is assumed to be the same as under ESHI.

[69]The results in this section are based on the estimates described in Section 6.2, which constrain the compensating wage differential parameter to $\gamma^S = -1$ (complete pass-through of ESHI cost; see Section 4.1). I also show a robustness check based on γ^S being unrestricted.

[70]Medicaid eligibility differs between mothers and children although the same threshold applies. This difference is due to a provision in PPACA that prohibits states to decrease Medicaid eligibility below the thresholds in place in 2010 until 2014 for adults and 2019 for children.

[71]Since the MEPS data stem from a 13 year period, I use the FPL that was in effect in the respective years to calculate the Medicaid eligibility threshold that enters the simulated health insurance coverages. In other words, Medicaid eligibility is imputed as if the health care reform had been in effect since 1996.

[72]I assume that everyone who is eligible to receive subsidies for health insurance also takes them up since there is an individual mandate under PPACA. However, PPACA also allows individuals to pay a tax of $\min\{\max\{\$695, 2.5\% \text{ of income}\}, \$2085\}$ per year if they are not covered by a health insurance plan. In future work, I will incorporate this policy into the simulations as well and allow for a choice between obtaining health insurance and paying the tax.

In addition to the utility arguments, I also simulate preference parameters by drawing 1000 times from the estimated distribution $\mathcal{N}\left(Z_i^u\hat{\delta}, \hat{\Sigma}\right)$ for each individual, where $\hat{\delta}$ and $\hat{\Sigma}$ are the estimated matrices reported in Table 13. Then I calculate the utility for every individual i, time period t, simulation draw r, and employment alternative j under policy pol, $U_{itj}^{pol,(r)}$, according to equation (19). The three policies considered are current Medicaid rules, PPACA Medicaid expansions only, and a combination of Medicaid expansions and health insurance subsidies.[73] For each individual, time period, and simulation draw, I calculate the alternative with the highest utility under each policy, and average over i, t, and r for each j:

$$\bar{d}_j^{pol} = \frac{1}{2NR}\sum_{i,t,r}\mathbf{1}\left\{j = \arg\max_k \; U_{itk}^{pol,(r)}, k = n, p, f_0, f_1\right\}, j = n, p, f_0, f_1.$$

The resulting choice fractions are reported in Table 15. I assess the model fit by comparing simulated choices under current Medicaid policies to actual choices in the first two columns of Table 15. Only the part-time employment alternatives shows a small significant difference between observed and simulated choice fractions. Hence, the model fits the observed choices well. In addition, I compare predicted and observed employment choices by state and year (see Figure 7). These graphs, in which each point corresponds to a state-year cell, show an overall good model fit. In particular, the model predicts non-work and full-time employment with ESHI well. The fit for part-time and full-time work without ESHI is a little less good since these two alternatives only differ in hours worked and are differentiated by an arbitrary cutoff (35 hours).

The second column in Table 15 shows that simulated choices under PPACA's Medicaid expansions only do not change substantially compared to current policies. The percentage of single mothers in the non-work alternative increases by 1.5 percentage points, full-time employment without ESHI increases by 0.5 percentage points, and full-time employment with ESHI decreases by two percentage points. The income effect of increased Medicaid eligibility outweighs the substitution effect, and this policy change leads to an overall decrease in labor supply. These simulation results are consistent with the reduced-form results reported in Section 6.1. Both sets of findings indicate that Medicaid expansions lead to work disincentives at the extensive margin and crowding-out of ESHI.

[73] By current policies, I mean the Medicaid eligibility thresholds for parents and children that were in place in the respective state of residence of the sample members in the years 1996 to 2008.

The last column in Table 15 contains the main result of this paper. Simulated employment fractions under both PPACA Medicaid expansions and health insurance subsidies reveal an increase in labor supply at the extensive and intensive margins and crowding-out of ESHI. The fraction choosing the non-work alternative decreases by almost two percentage points compared to current Medicaid rules, which corresponds to a six percent decrease. In addition, there is an increase in labor supply at the intensive margin: part-time work decreases by two percentage points and full-time work without ESHI almost doubles from 22 to 38 percent. Hence, labor supply increases by five percent at the intensive margin. Finally, there is substitution of Medicaid and subsidized health insurance for ESHI since full-time employment with ESHI decreases by almost 13 percentage points. Therefore, adding health insurance subsidies beyond the Medicaid eligibility threshold leads to a decrease in the Medicaid "notch" that is sufficient to increase labor supply as predicted in Section 7.1. Moreover, subsidized health insurance constitutes a valuable alternative to ESHI.[74]

In Table 16, I show the same statistics as in Table 15 broken down by individual characteristics to assess the amount of heterogeneity in my simulation results. I focus on the policy simulation with Medicaid expansions and health insurance subsidies here (corresponding to the final column in Table 16). Comparing panels (a.1) and (a.2) reveals that the increase in labor force participation and the crowding-out of ESHI are mostly concentrated among single mothers without young children. Panels (b.1) and (b.2) show that single mothers with medical conditions react more strongly to health care reform. In particular, they are more likely to work full-time without ESHI and more likely to enter the labor force. Hence, health care reform allows women with a higher need for health insurance to obtain subsidized health insurance instead of relying on ESHI. These single mothers benefit from health care reform not only because they gain access to health insurance, but also because the reform reduces restrictions in employment choice to not work at all or to work full-time with ESHI. The difference between the simulated employment choices of single mothers with children with and without medical conditions is very small (see panels (c.1) and (c.2) in Table 16). Finally, panels (d.1) and (d.2) show that mostly single mothers whose income is above the median increase their labor supply.

Table 17 contains transition matrices that show the simulated percentages of single mothers switching employment alternatives due to health care reform. Panel (a) shows that at most 15

[74] While the simulation results presented here are based on the assumption of complete pass-through of ESHI cost ($\gamma^S = -1$ in equation (9)), Table A2 contains the same statistics as Table 15 using estimates that do not restrict γ^S. In this case the estimate is $\hat{\gamma}^S = 0.25$. Table A2 shows that the policy simulations are overall robust to a wide range of values for the compensating differential parameters.

percent switch out of their initial employment alternative when only Medicaid expansions are introduced. About six percent change from part-time and full-time work without ESHI, respectively, to the non-work alternative. Five percent move from part-time and eight percent switch from full-time work with ESHI, respectively, into full-time employment without ESHI. The fractions of single mothers changing their employment choice under PPACA with Medicaid expansions and health insurance subsidies are higher (see panel (b)). These results show that the increase in labor supply comes mostly from women moving from part-time to full-time work (25 percent) with a sizable fraction of women moving from non-work (12 percent) directly into full-time employment without ESHI. Moreover, the substantial crowding-out of ESHI without reducing labor supply (40 percent) is also visible in this table.

Finally, I asses the welfare implications of these changes in single mothers' employment decisions due to health care reform. I account for three types of costs: government transfers (welfare, food stamps, and taxes), Medicaid, and health insurance subsidies.[75] Panel (a) of Table 18 contains the per-family averages of these costs under current Medicaid policies and PPACA (consisting of Medicaid expansions and subsidized health insurance). Total average per-family government expenditure is about \$9,200 under current policies and \$11,000 under PPACA (in 2008 dollars). This cost increase stems from the introduction of health insurance subsidies. Medicaid payments decrease under PPACA, and transfers are also lower since the increase in labor supply leads to lower welfare payments and higher tax revenue. Overall, health care reform leads to a cost increase of about \$1,800 per family.

The costs of this reform are offset by the much higher willingness of single mothers to give up consumption. The average compensating variation for this policy change is about –\$6,500 as shown in panel (b) of Table 18.[76] That is, reducing families' consumption under PPACA by this amount on average equates utility pre and post reform. To the extent that additional taxation does not adversely affect behavior, the government could collect the required \$1,800 per family to make this reform revenue neutral while still increasing average welfare. Raising taxes would lead to decreased work incentives, which would reduce the welfare gains from health care reform, but

[75] Average transfers are shown in Table 11, panel (a). For Medicaid costs, I use average yearly per-capita payments for adults and children from the CMS (https://www.cms.gov/MedicareMedicaidStatSupp/09_2010.asp, Tables 13.13 and 13.14). The cost of health insurance subsidies are equal to average ESHI costs by year and state minus the maximum paid by individuals according to the sliding scale in Table 1.

[76] I calculate the compensating variation (CV) such that simulated utility under current Medicaid policies is equal to utility under PPACA when consumption is increased or reduced by the CV. Since the utility function in quadratic, there is a closed-form solution for CV.

since the compensating variation is almost four times as large as the additional expenditure, it is likely that the positive welfare effects would remain.

8 Discussion and Conclusion

This paper assesses the employment effects of the Medicaid expansions and health insurance subsidies under PPACA among single mothers. To this end, I estimate a structural model of labor supply model on a sample of single mothers from the MEPS, exploiting variation in Medicaid eligibility thresholds across states and time.

The simulated employment choices show that Medicaid expansions and premium subsidies have two main effects. They increase labor force participation by six percent and raise labor supply at the intensive margin by five percent. In addition, I find crowding-out of ESHI amounting to 40 percent. The latter finding is consistent with the literature. For example, Cutler and Gruber (1996) find substantial crowding-out of ESHI in response to Medicaid expansion for children and pregnant women. In contrast, Blumberg et al. (2011) argue that PPACA will not lead to a significant drop in ESHI coverage. However, they consider the entire labor force, not just single mothers. The latter constitutes a group that benefits particularly from cheaper alternatives to ESHI and is therefore expected to change behavior accordingly, which is reflected in my results.

My simulation results reveal considerable heterogeneity in single mothers' employment choice under health care reform. In particular, women with a higher demand for health insurance due to medical conditions increase their labor supply more and are more likely to drop ESHI. This result shows that single mothers, whose need for health insurance coverage currently restricts their employment choice to not working or working full-time with ESHI, can switch to a better employment option while retaining health insurance coverage.

In contrast to the predictions made by the Congressional Budget Office for the whole labor force (see Section 2.2), my policy simulations show that single mothers will work more rather than less when PPACA comes into effect. The six percent increase in labor supply at the extensive margin implies that 18,000 single mothers will enter the labor force compared to the overall drop in employment by 800,000 individuals predicted by the CBO. This result is important because single mothers constitute a particularly vulnerable population with limited access to health insurance. Health care reform is designed to reduce this lack of health insurance, but might be expected to lead to work disincentives. This would make the reform more expensive as women who are driven out of the labor force would rely on welfare. My simulation results show that this scenario will not occur under health care reform. Hence, health care reform achieves two policy goals: reducing the number of uninsured individuals and providing incentives for increased labor supply in this population.

A comparison of the costs and benefits of this reform reveals positive implications for average welfare. However, a definite answer to the question of if health care reform is welfare improving would have to incorporate the taxes necessary to pay for Medicaid and health insurance subsidies. Since increased taxes would lead to lower labor supply, the estimates provided in Table 18 are an upper limit for the average welfare gain.

The results presented here only apply to single mothers and cannot easily be extended to other groups. In particular, the low average earnings even when working full-time imply that there is no work disincentive at the income cutoff when eligibility for health insurance subsidies ends. Hence, the simulated increase in full-time work among single mothers may not carry over to other groups. Nevertheless, these results are policy relevant in their own right.

The simulation results in this paper rely on a static labor supply model and hence cannot account for general equilibrium effects or dynamics. PPACA contains provisions that directly affect the demand side of the labor market, in particular employer mandates. An equilibrium model such as the one proposed by Dey and Flinn (2005) could account for the effects of these provisions in addition to the ones considered in this paper. Since employers will face penalties if they do not provide ESHI to their employees or if their workers obtain subsidized health insurance, they are more likely to offer health benefits. Hence, my results provide an upper bound on the crowding-out of ESHI. However, the focus in this paper is on single mothers and not on the entire workforce so that a partial analysis of the labor market is justified.

A static model does not account for job search or human capital accumulation. With job search, the simulated employment changes would be attenuated since it might not be possible for a single mother to immediately find a job when Medicaid expansions allow her to enter the labor force. Dynamic optimization that includes the effects of contemporaneous labor supply on future earnings through human capital accumulation may also affect the results. In particular, the work incentives would be larger before the health care reform, so increasing health insurance availability may have a relatively smaller impact on benefits from working, thereby reducing the labor supply response. Since single mothers are often marginally attached to the labor market; however, they may consider future earnings less than other groups when making employment choices.

The limitations of this paper lead themselves to extensions for future work. To generalize my results, I will broaden the analysis to include other populations. Methodologically, it will be valuable to simulate employment choice in an equilibrium model of the labor market that incorporates employer mandates. Finally, I will augment the framework by including dynamic components, such as search and human capital accumulation.

A Appendix: Wage Selection Correction

This appendix contains details about the selection correction procedure for the wage equation (see Section 4.1). Equations (9), (10), and (11) define the model. Let $W_{it} = \left(Z_{it}^{w}, Z_{it}^{L}, Z_{it}^{S}\right)$ denote all observables entering the wage equation and the two selection equations. $W_i = (W_{i1}, W_{i2})$ collects these variables for individual i for both time periods $t = 1, 2$. The time specific error terms in the two selection equations and the wage equation have a joint trivariate normal distribution:

$$\begin{bmatrix} u_{it}^{L} \\ u_{it}^{S} \\ u_{it}^{w} \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_L^2 & \rho_{LS} & \rho_{Lw} \\ \rho_{LS} & \sigma_S^2 & \rho_{Sw} \\ \rho_{Lw} & \rho_{Sw} & \sigma_w^2 \end{bmatrix} \right). \tag{24}$$

I assume that the unobserved effects in the selection equations for LFP and ESHI, (10) and (11) are correlated random effects:

$$a_i^h = Z_{i1}^{h\prime}\psi_1^h + Z_{i2}^{h\prime}\psi_2^h + \nu_i^h, h = L, S$$

and that $\nu_i^h \sim \mathcal{N}\left(0, 1 - \sigma_h^2\right)$ without loss of generality and ν_i^h is independent of everything else. Hence the composite error term in the two selection equations has a standard normal distribution: $e_{it}^h = \nu_i^h + u_{it}^h \sim \mathcal{N}(0, 1)$. With these distributional assumptions, I estimate the selection equations via bivariate probit with incomplete observability:

$$\Pr\left(\{L_{it} = 1\}, \left\{I_{it}^S = 1 | L_{it} = 1\right\}\right) = \mathbf{\Phi}\left(Z_{it}^{L\prime}\delta^L + \bar{Z}_i^{L\prime}\psi^L, Z_{it}^{S\prime}\delta^S + \bar{Z}_i^{S\prime}\psi^S, \rho_{LS}\right),$$

where $\mathbf{\Phi}(\cdot,\cdot,\rho)$ is the c.d.f. of the bivariate normal distribution with correlation parameter ρ_{LS}. Since there are only two time periods, using the within individual means $\bar{Z}_i^h$ is equivalent to adding both time-specific vectors, Z_{i1}^h and $Z_{i2}^h, h = L, S$.

For the unobserved effect in the wage equation (9), I make the following assumption:

$$\mathbb{E}\left[a_i^w | W_i, e_{it}^L, e_{it}^S\right] = Z_{i1}^{w\prime}\psi_1^w + Z_{i2}^{w\prime}\psi_2^w + \mu_t^L e_{it}^L + \mu_t^S e_{it}^S. \tag{25}$$

Hence, the unobserved wage heterogeneity term is a linear projection of the wage equation observables for both time periods and the composite error terms from the selection equations, $e_{it}^h, h = L, S$. This assumption is equivalent to Assumption 3'(ii) in Wooldridge (1995) with the difference that equation (25) accounts for two selection equations whereas there is one selection equation in Wooldridge (1995). In addition, the following conditional expectation of the wage equation error term follows from the distributional assumption (24):

$$\begin{aligned}
\mathbb{E}\left[u_{it}^w | W_i, e_{it}^L, e_{it}^S\right] &= \frac{\sigma_S^2 \rho_{Lw} - \rho_{LS}\rho_{Sw}}{\sigma_L^2\sigma_S^2 - \rho_{LS}^2} e_{it}^L + \frac{\sigma_L^2 \rho_{Sw} - \rho_{LS}\rho_{Lw}}{\sigma_L^2\sigma_S^2 - \rho_{LS}^2} e_{it}^S \\
&= \tilde{\rho}_{Lw} e_{it}^L + \tilde{\rho}_{Sw} e_{it}^S.
\end{aligned}$$

With these assumptions, I now derive the conditional expectations of the natural logarithm of the wage for jobs with ($I_{it}^S = 1$) and without ($I_{it}^S = 0$) ESHI. Since wages are only observed if an individual is employed, $L_{it} = 1$ in both cases.

$$\begin{aligned}
\mathbb{E}\left[\ln w_{it} | W_i, L_{it} = 1, I_{it}^S = 1\right] &= \mathbb{E}\left[\ln w_{it} | W_i, e_{it}^L > -Z_{it}^{L\prime}\delta^L - \bar{Z}_i^{L\prime}\psi^L,\right. \\
&\qquad \left. e_{it}^S > -Z_{it}^{S\prime}\delta^S - \bar{Z}_i^{S\prime}\psi^S\right] \\
&= \gamma^S SC_{it} + Z_{it}^{w\prime}\gamma^w \\
&\quad + \mathbb{E}\left[a_i^w | W_i, e_{it}^L > -Z_{it}^{L\prime}\delta^L - \bar{Z}_i^{L\prime}\psi^L, e_{it}^S > -Z_{it}^{S\prime}\delta^S - \bar{Z}_i^{S\prime}\psi^S\right] \\
&\quad + \mathbb{E}\left[u_{it}^w | W_i, e_{it}^L > -Z_{it}^{L\prime}\delta^L - \bar{Z}_i^{L\prime}\psi^L, e_{it}^S > -Z_{it}^{S\prime}\delta^S - \bar{Z}_i^{S\prime}\psi^S\right] \\
&= \gamma^S SC_{it} + Z_{it}^{w\prime}\gamma^w + Z_{i1}^{w\prime}\psi_1^w + Z_{i2}^{w\prime}\psi_2^w + \left(\mu_t^L + \tilde{\rho}_{Lw}\right)\lambda_{it}^{11,L} \\
&\quad + \left(\mu_t^S + \tilde{\rho}_{Sw}\right)\lambda_{it}^{11,S},
\end{aligned} \tag{26}$$

where the last equality is from (Tunali, 1986, p. 273). Tunali (1986) also gives the expressions for the selection correction terms $\lambda_{it}^{11,L}$ and $\lambda_{it}^{11,S}$:

$$\lambda_{it}^{11,L} = \frac{\phi\left(Z_{it}^{L}\delta^{L} + \bar{Z}_{i}^{L\prime}\psi^{L}\right)\Phi\left(\frac{Z_{it}^{S}\delta^{S} + \bar{Z}_{i}^{S\prime}\psi^{S} - \rho\left(Z_{it}^{L}\delta^{L} + \bar{Z}_{i}^{L\prime}\psi^{L}\right)}{\sqrt{1-\rho^{2}}}\right)}{\mathbf{\Phi}\left(Z_{it}^{L}\delta^{L} + \bar{Z}_{i}^{L\prime}\psi^{L}, Z_{it}^{S}\delta^{S} + \bar{Z}_{i}^{S\prime}\psi^{S}, \rho\right)} \tag{27}$$

and

$$\lambda_{it}^{11,S} = \frac{\phi\left(Z_{it}^{S}\delta^{S} + \bar{Z}_{i}^{S\prime}\psi^{S}\right)\Phi\left(\frac{Z_{it}^{L}\delta^{L} + \bar{Z}_{i}^{L\prime}\psi^{L} - \rho\left(Z_{it}^{S}\delta^{S} + \bar{Z}_{i}^{S\prime}\psi^{S}\right)}{\sqrt{1-\rho^{2}}}\right)}{\mathbf{\Phi}\left(Z_{it}^{L}\delta^{L} + \bar{Z}_{i}^{L\prime}\psi^{L}, Z_{it}^{S}\delta^{S} + \bar{Z}_{i}^{S\prime}\psi^{S}, \rho\right)}, \tag{28}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the p.d.f. and the c.d.f. of the univariate standard normal distribution, respectively, and $\mathbf{\Phi}(\cdot,\cdot,\rho)$ is the c.d.f. of the bivariate normal distribution as above. Similarly, the conditional expectation of log-wage for jobs without ESHI ($I_{it}^{S} = 0$) is

$$\begin{aligned}
\mathbb{E}\left[\ln w_{it} | W_i, L_{it} = 1, I_{it}^{S} = 1\right] &= \mathbb{E}\left[\ln w_{it} | W_i, e_{it}^{L} > -Z_{it}^{L\prime}\delta^{L} - \bar{Z}_{i}^{L\prime}\psi^{L},\right. \\
&\qquad \left. e_{it}^{S} \leq -Z_{it}^{S\prime}\delta^{S} - \bar{Z}_{i}^{S\prime}\psi^{S}\right] \\
&= Z_{it}^{w\prime}\gamma^{w} \\
&\quad + \mathbb{E}\left[a_{i}^{w} | W_i, e_{it}^{L} > -Z_{it}^{L\prime}\delta^{L} - \bar{Z}_{i}^{L\prime}\psi^{L}, e_{it}^{S} \leq -Z_{it}^{S\prime}\delta^{S} - \bar{Z}_{i}^{S\prime}\psi^{S}\right] \\
&\quad + \mathbb{E}\left[u_{it}^{w} | W_i, e_{it}^{L} > -Z_{it}^{L\prime}\delta^{L} - \bar{Z}_{i}^{L\prime}\psi^{L}, e_{it}^{S} \leq -Z_{it}^{S\prime}\delta^{S} - \bar{Z}_{i}^{S\prime}\psi^{S}\right] \\
&= Z_{it}^{w\prime}\gamma^{w} + Z_{i1}^{w\prime}\psi_{1}^{w} + Z_{i2}^{w\prime}\psi_{2}^{w} + \left(\mu_{t}^{L} + \tilde{\rho}_{Lw}\right)\lambda_{it}^{10,L} \\
&\quad + \left(\mu_{t}^{S} + \tilde{\rho}_{Sw}\right)\lambda_{it}^{10,S}
\end{aligned} \tag{29}$$

with

$$\lambda_{it}^{10,L} = \frac{\phi\left(Z_{it}^{L}\delta^{L} + \bar{Z}_{i}^{L\prime}\psi^{L}\right)\Phi\left(-\frac{Z_{it}^{S}\delta^{S} + \bar{Z}_{i}^{S\prime}\psi^{S} - \rho\left(Z_{it}^{L}\delta^{L} + \bar{Z}_{i}^{L\prime}\psi^{L}\right)}{\sqrt{1-\rho^{2}}}\right)}{\Phi\left(Z_{it}^{L}\delta^{L} + \bar{Z}_{i}^{L\prime}\psi^{L}, -Z_{it}^{S}\delta^{S} - \bar{Z}_{i}^{S\prime}\psi^{S}, -\rho\right)} \tag{30}$$

and

$$\lambda_{it}^{10,S} = -\frac{\phi\left(Z_{it}^{S}\delta^{S} + \bar{Z}_{i}^{S\prime}\psi^{S}\right)\Phi\left(\frac{Z_{it}^{L}\delta^{L} + \bar{Z}_{i}^{L\prime}\psi^{L} - \rho\left(Z_{it}^{S}\delta^{S} + \bar{Z}_{i}^{S\prime}\psi^{S}\right)}{\sqrt{1-\rho^{2}}}\right)}{\Phi\left(Z_{it}^{L}\delta^{L} + \bar{Z}_{i}^{L\prime}\psi^{L}, -Z_{it}^{S}\delta^{S} - \bar{Z}_{i}^{S\prime}\psi^{S}, -\rho\right)}. \tag{31}$$

To estimate the coefficients of the wage equation, I plug the estimated coefficients from the bivariate probit, $\hat{\delta}^{h}$ and $\hat{\psi}^{h}, h = L, S$ and the estimated correlation $\hat{\rho}$ into the four selection correction terms (27), (28), (30), and (31) to obtain the estimates $\hat{\lambda}_{it}^{11,L}$, $\hat{\lambda}_{it}^{11,S}$, $\hat{\lambda}_{it}^{10,L}$, and $\hat{\lambda}_{it}^{10,S}$. Then, I use the conditional expectations (26) and (29) to generate the wage regression (see equation

(12) in Section 4.1). Instead of including the wage equation regressors for both periods $t = 1, 2$ (i.e., Z_{i1}^w and Z_{i2}^w), I use the within-individual mean of these regressors, denoted by $\bar{Z}_i^w$. Since there are only two time periods, this substitution is equivalent to the original expression. Instead of estimating equations (26) and (29) separately, I multiply the former by the indicator I_{it}^S and the latter by $1 - I_{it}^S$ and estimate them jointly. This is possible because the time specific wage shock is the same for jobs with and without ESHI coverage. Moreover, since I estimate a bivariate probit separately for each time period, the resulting selection correction terms (the λs) are time specific. To account for this time variation in a pooled OLS regression of wages for both periods, I multiply the selection correction terms for the second period by a period dummy $T_{it}^2 = \mathbf{1}\{t = 2\}$. Adding these interactions yields the regression (12).

Table A1 shows the estimates from the bivariate probit of LFP and ESHI for each in the two time periods. Since the estimation uses two observations for each individual, the means are often close to the period-specific regressors. Therefore, the within-individual means may pick up the effect of the time-varying regressors and the estimates should be interpreted accordingly in this and the other first-step regressions. The results in Table A1 show some evidence that single mothers with medical conditions, younger children, and children who have medical conditions are less likely to participate in the labor force. Conditional on working, these variables do not significantly affect the propensity of ESHI coverage however. In addition, single mothers with higher eduction are more likely to be in the labor force and hold a job with ESHI and there is an inverse-U shaped age profile in both LFP and ESHI coverage. Among the state-level variables, only the average fraction of firms offering ESHI has a significant (positive) impact on obtaining ESHI while Medicaid eligibility thresholds for both mothers and children have virtually no effect on both outcomes.

B Appendix: Government Program Policies and Data Sources

B.1 Medicaid

I show and describe the Medicaid eligibility rules for parents and children in the text (see equations (5) and (6)). The Medicaid eligibility thresholds for parents and children in different age groups,

M_{it}^{P} and $M_{it}^{K,a}$, differ by state, year, and family size and completely describe the eligibility for this program.[77]

B.2 TANF

TANF rules are set by states and—with some simplifications—can be of either of two types:

$$TANF_{stf} = \max\left\{RP_{st}\left[BENSTD_{stf} - (E - DISREG_{st})\right], 0\right\}$$

or

$$TANF_{stf} = \min\left\{\max\left\{RP_{st}\left[BENSTD_{stf} - (E - DISREG_{st})\right], 0\right\}, MAXBEN_{stf}\right\},$$

in state s, year t, and family size f, where RP_{st} is the ratable percentage (which can be above or below one), $BENSTD_{stf}$ is the benefit standard, E are monthly earnings, $DISREG_{st}$ is an earnings disregard, which can be expressed either as a dollar amount or a percentage, and $MAXBEN_{stf}$ is the maximum benefit. $BENSTD_{stf}$ and $MAXBEN_{stf}$ vary by family size. These rules are somewhat simplified, but capture the calculation of welfare benefits in most states accurately.[78]

In addition, there are requirements that families have to meet in order to be eligible for TANF. Most states have gross and net income or earnings tests, for example. In many cases, these tests coincide with the benefit calculation, i.e., families are eligible if $TANF_{stf} > 0$. Moreover, some states also impose asset tests. Since the MEPS data do not contain information on respondents' assets, I do not incorporate asset tests when imputing welfare benefits.

B.3 Food Stamps

Eligibility is determined by gross and net income tests. To be eligible, gross monthly income (GMI) has to be below 1.3 times the FPL, where GMI is defined as most cash income including TANF benefits and excludes non-cash and in-kind income. I assume that households have no unearned

[77] Sources for Medicaid thresholds: Sarah Hamersma kindly shared thresholds for parental Medicaid with me (see also Hamersma and Kim, 2009); for children's Medicaid: Kaiser Commission on Medicaid and the Uninsured, "A 50 State Update on Eligibility Rules, Enrollment and Renewal Procedures, and Cost-Sharing Practices in Medicaid and SCHIP," various years (available at http://www.kff.org/medicaid/index.cfm).

[78] Source for TANF parameters: Urban Institute Welfare Rules Database (http://anfdata.urban.org/wrd/wrdwelcome.cfm).

income so that GMI equals monthly family earnings plus TANF benefits. In addition, net monthly income (NMI) has to be below the FPL. NMI equals GMI minus the standard deduction (between \$134 and \$191 according to family size), 20 percent of earnings, the dependent care deduction (\$200 for under two year olds, \$175 for over two year olds), the medical deduction (maximum \$35), a child support payment deduction (assumed to be zero), and an excess shelter deduction (maximum from \$247 in 1996 to \$431 in 2008). To simplify the calculation, I assume that all children are over two years old and set the medical and excess shelter deductions equal to their maximum amounts. Benefits are calculated as maximum benefit, which varies by family size, minus 0.3 times NMI. The food stamp program is a federal program so that benefits do not vary across states, but only over time.[79]

B.4 Earned Income Tax Credit (EITC)

The following parameters vary by number of children: credit rate (r_c^n), minimum income for maximum credit (Y_{min}^n), maximum credit (C_{max}^n), phaseout rate (r_p^n), beginning income for phaseout (Y_{beg}^n), and ending income for phaseout (Y_{end}^n), where $n = 0, 1, 2$ is the number of children (0, 1, and 2 or more).[80] The monthly tax credit given monthly earnings E is defined as

$$
\begin{aligned}
EITC = \frac{1}{12} \big[r_c^n 12E \mathbf{1} \left\{ 0 < 12E \leq Y_{min}^n \right\} + C_{max}^n \mathbf{1} \left\{ Y_{min}^n < 12E \leq Y_{beg}^n \right\} \\
+ \left[C_{max}^n - r_p^n \left(12E - Y_{beg}^n \right) \right] \mathbf{1} \left\{ Y_{beg}^n < 12E \leq Y_{end}^n \right\} \big] .
\end{aligned}
$$

Hence, a family is not eligible to receive the EITC if annual earnings are zero or exceed Y_{end}

B.5 Federal Income and Payroll Taxes

Annual taxable income is defined as

$$TI = 12E - ded_s - fs \times exem,$$

[79] Source for food stamp parameters: United States Department of Agriculture: Characteristics of Food Stamp Households, Fiscal Years 1996 to 2007, Characteristics of Supplemental Nutrition Assistance Program Households, Fiscal Year 2008. Available from http://www.fns.usda.gov/. Federal poverty line data available from http://aspe.hhs.gov/poverty/figures-fed-reg.shtml.

[80] Source for EITC variables: Tax Policy Center Historical EITC Parameters (http://www.taxpolicycenter.org/taxfacts/Content/PDF/historical_eitc_parameters.pdf).

where E is monthly earnings, ded_s is the standard deduction, which varies by filing status, fs is family size, and $exem$ is the personal exemption. Possible filing status are single, married filing jointly, and head of household. MEPS data contain a variable that indicates a single mother's filing status. (She might file as married filing jointly if she is not yet divorced, for example.) Monthly tax payments are defined as

$$FIT = \frac{1}{12} \sum_{i=1}^{I} \tau_i \max \left\{ \min \left\{ TI - F_{i-1}^s, F_i^s - F_{i-1}^s \right\}, 0 \right\},$$

where $I = 5$ (until 2001) or $I = 6$ (2002 and later) is the number of income brackets, τ_i is the tax rate in bracket i, F_i^s is the end point of bracket i, $F_0^s = 0$, and $F_I^s = \infty$. The bracket end points but not the tax rates depend on filing status.[81]

The payroll tax between 1996 and 2008 was 7.65 percent (6.2 percent employee contribution to the Old-Age, Survivors, and Disability program and 1.45 percent for Medicare).[82]

B.6 Other Data Sources

Besides the policy variables described in this appendix I also use some other state-level variables. Fractions of firms offering ESHI, average ESHI premiums, and fractions of the premium paid by employers and employees, respectively, come from the Insurance Component (IC) of the MEPS. Summary statistics of the MEPS IC data at the state and year level are publicly available.[83] I obtain state unemployment rates and the consumer price index from the Bureau of Labor Statistics.[84] Finally, state minimum wages come from the Department of Labor.[85]

[81] Source for federal income tax variables: Tax Policy Center Individual Income Tax Parameters (Including Brackets), 1945-2011 (http://www.taxpolicycenter.org/taxfacts/Content/PDF/individual_rates.pdf).

[82] Source: Tax Policy Center Historical Social Security Tax Rates (http://www.taxpolicycenter.org/taxfacts/Content/PDF/ssrate_historical.pdf)

[83] Source: Agency for Healthcare Research and Quality, Center for Financing, Access and Cost Trends. 1996 to 2006, 2008 Medical Expenditure Panel Survey-Insurance Component (http://www.meps.ahrq.gov/mepsweb/data_stats/quick_tables_search.jsp?component=2&subcomponent=2). There was no data collection in 2007 so that I use the average between 2006 and 2008.

[84] Sources: Bureau of Labor Statistics: Local Area Unemployment Statistics (http://www.bls.gov/lau/) and Consumer Price Index (ftp://ftp.bls.gov/pub/special.requests/cpi/cpiai.txt).

[85] Source: United States Department of Labor: Changes in Basic Minimum Wages in Non-Farm Employment Under State Law: Selected Years 1968 to 2008 (http://www.dol.gov/whd/state/stateMinWageHis.htm).

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Figures

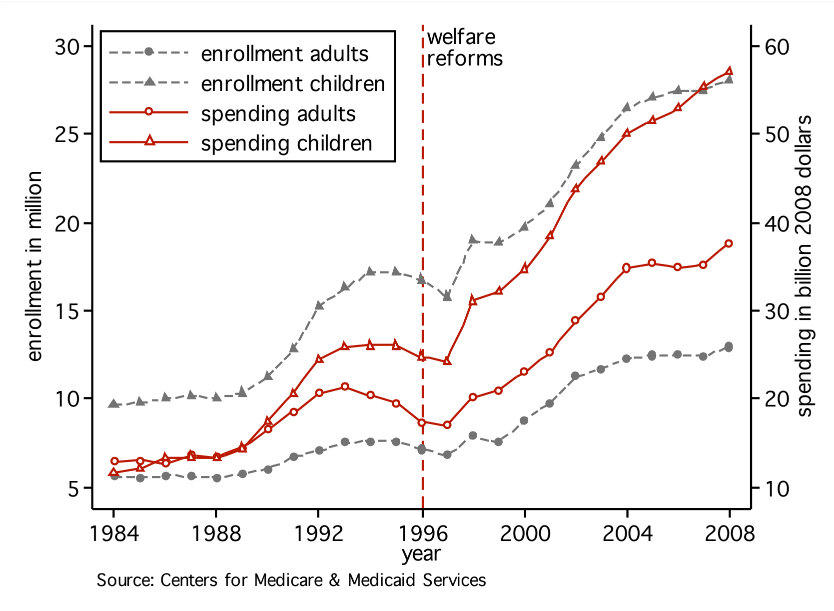


Figure 1: **Medicaid Enrollment and Spending**

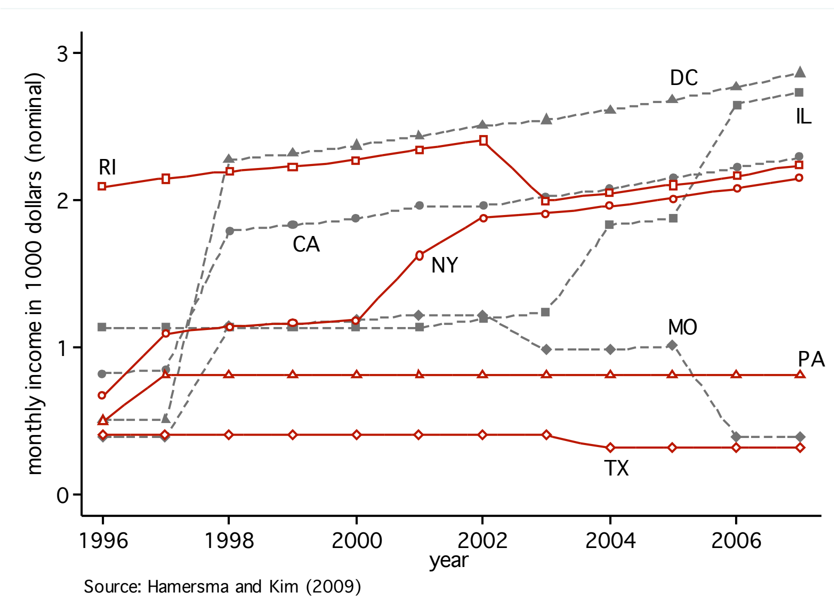


Figure 2: **Monthly Parental Medicaid Eligibility Thresholds for a Family of Three for Exemplary States**

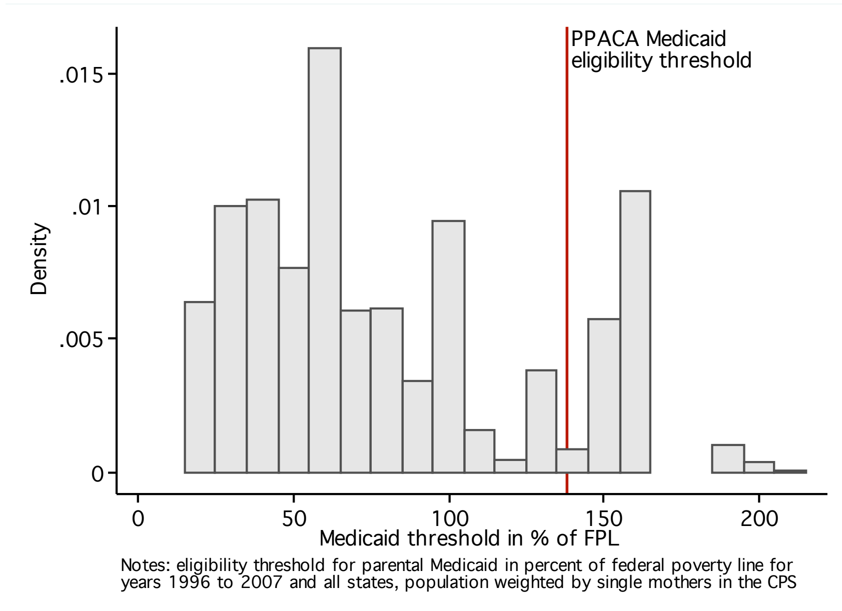


Figure 3: **Distribution of Eligibility Thresholds for Parental Medicaid**

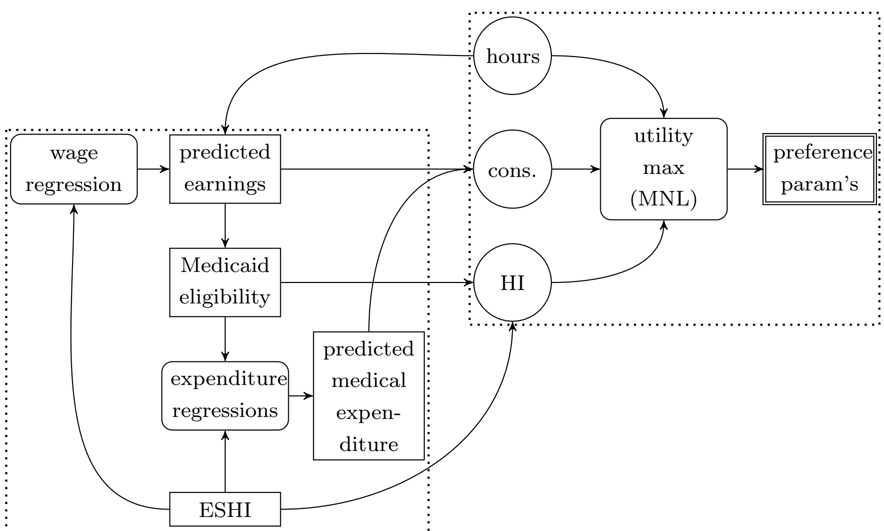
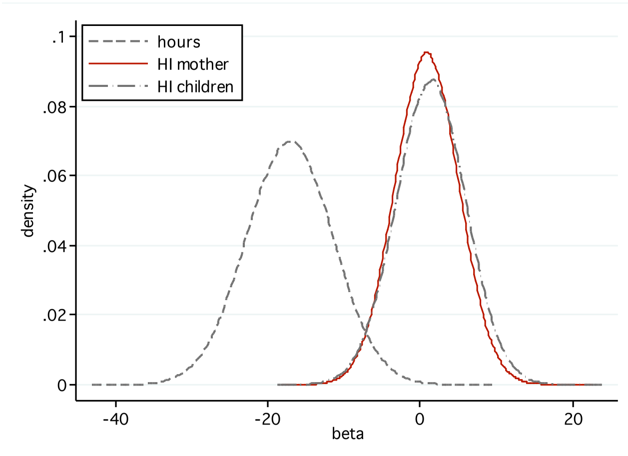
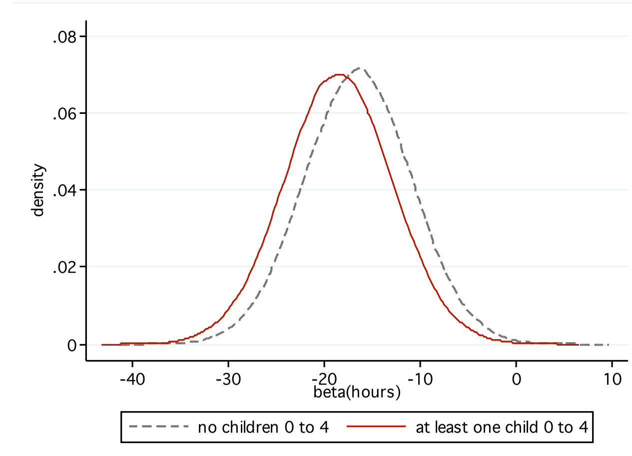


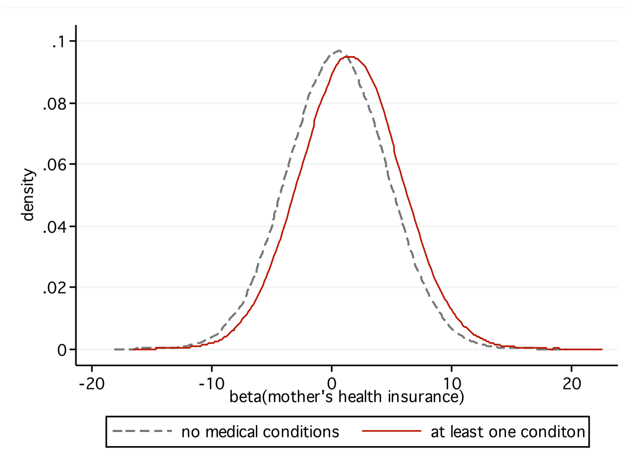
Figure 4: **Estimation Flow Chart**



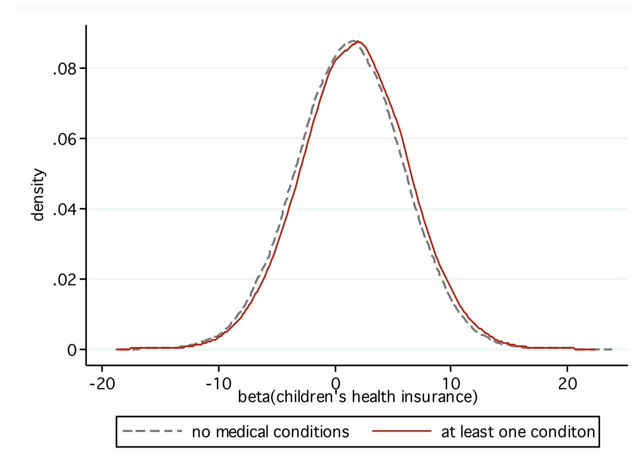
(a) **Estimated Distribution of All Preference Parameters**



(b) **Estimated Distribution of Preference Parameters for Hours Worked by Number of Young Children**

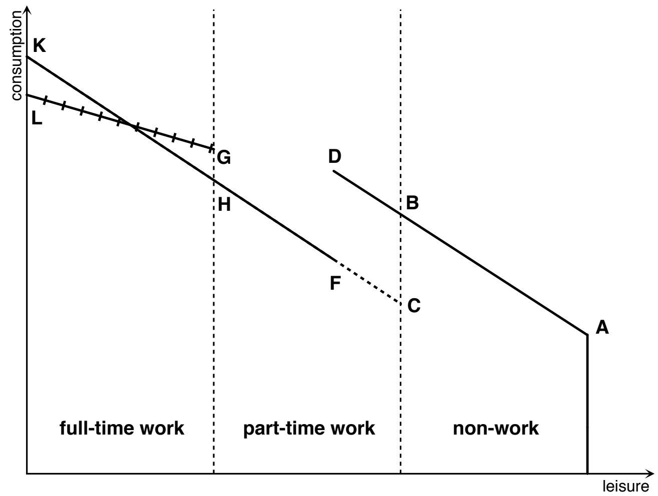


(c) **Estimated Distribution of Preference Parameters for Mothers' Health Insurance by Mothers' Medical Conditions**

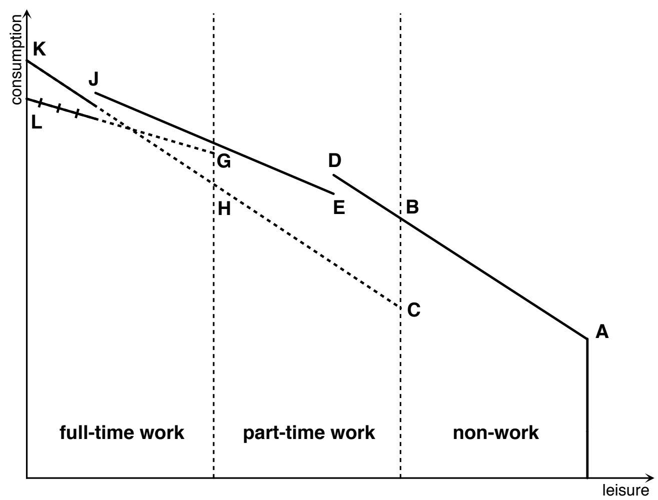


(d) **Estimated Distribution of Preference Parameters for Children's Health Insurance by Children's Medical Conditions**

Figure 5: **Estimated Distribution of Preference Parameters**

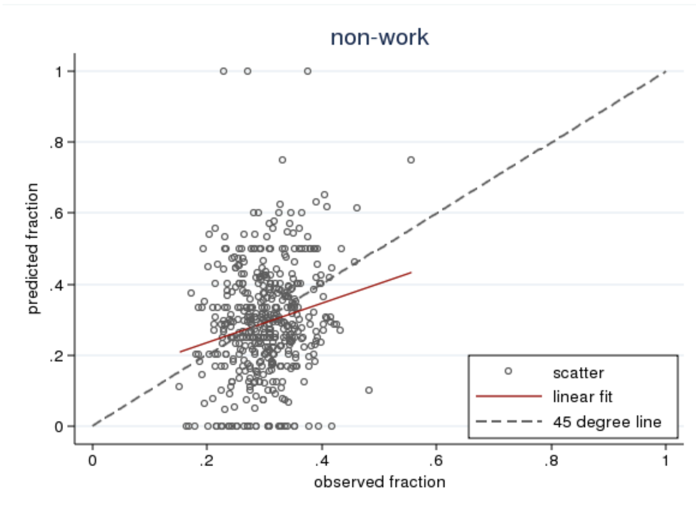


(a) **Under Medicaid Expansion Only**

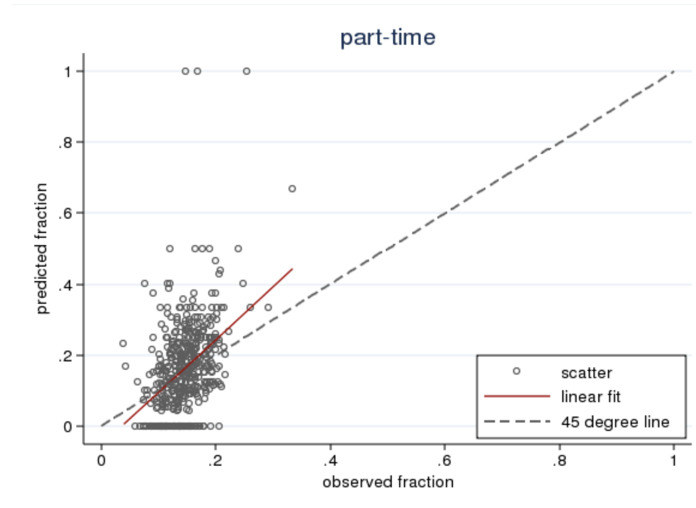


(b) **Under Medicaid Expansion and Health Insurance Subsidies**

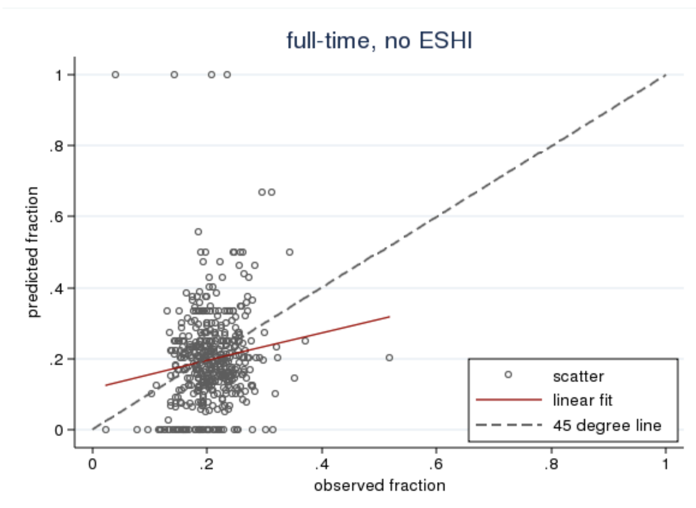
Figure 6: **Budget Sets Under Health Care Reform**



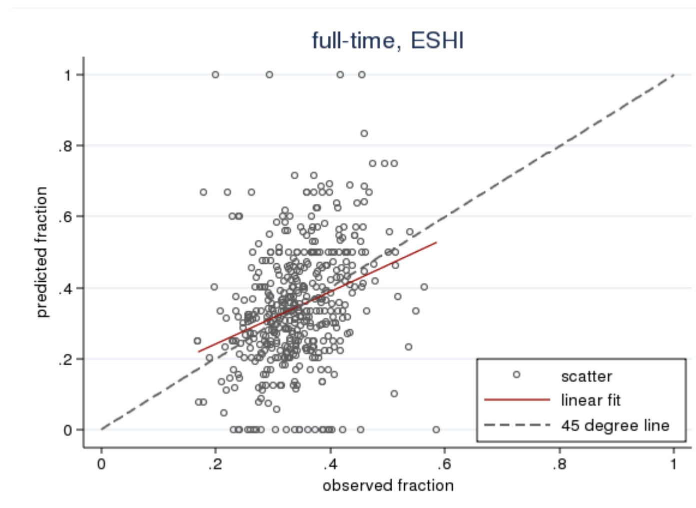
(a) **Non-Work**



(b) **Part-Time Work**



(c) **Full-Time Work Without ESHI**



(d) **Full-Time Work With ESHI**

Figure 7: **Scatter Plots of Average (by State and Year) Observed and Predicted Employment Choices**

Tables

Table 3: **Regressors Included in Wage and Medical Expenditure Equations**

	wage equation Z_{it}^w	LFP selection equation Z_{it}^L	ESHI selection equation Z_{it}^S	mother's med. expenditure Z_{it}^P	children's med. expenditure Z_{it}^K
individual-level variables					
quadratic in mother's age	X	X	X	X	
black, Hispanic	X	X	X	X	X
education	X	X	X	X	X
any/# of med. conditions, mother	X	X	X	X	
any/# of med. conditions, children		X	X		X
# of children in different age groups		X			X
predicted Medicaid eligibility				X	X
state-level variables					
ESHI cost to employer	X				
ESHI cost to employee			X		
ESHI availability			X		
unemployment rate	X				
minimum wage	X				
Medicaid eligibility thresholds		X	X		

Note: this table shows which independent variables are included in the wage and medical expenditure equations of the first estimation step.

Table 4: **Means and Standard Deviations (in Parentheses) of Individual Characteristics by Employment Choice**

	non-work	part-time	full-time, no ESHI	full-time, ESHI
frequency	3,181	1,651	2,049	3,397
percent	30.9	16.1	19.9	33.1
age	34.75	34.59	34.28	38.05
	(9.01)	(8.53)	(8.10)	(7.65)
black	0.388	0.364	0.349	0.353
Hispanic	0.333	0.234	0.345	0.197
years of education	10.97	11.96	11.54	13.10
	(2.69)	(2.53)	(2.54)	(2.41)
number of children	2.08	1.91	1.99	1.65
	(1.08)	(0.99)	(0.99)	(0.81)
-- aged 0 to 2	0.32	0.22	0.22	0.10
	(0.57)	(0.48)	(0.46)	(0.32)
-- aged 3 to 4	0.24	0.22	0.21	0.12
	(0.46)	(0.45)	(0.43)	(0.34)
-- aged 5 to 10	0.72	0.68	0.71	0.54
	(0.83)	(0.78)	(0.80)	(0.69)
-- aged 11 and older	0.80	0.78	0.85	0.89
	(0.91)	(0.94)	(0.94)	(0.82)
age of youngest child	7.05	7.49	7.52	9.67
	(5.42)	(5.04)	(5.05)	(5.01)
any med. cond., mother	0.531	0.399	0.393	0.423
# of med. cond., mother	1.258	0.714	0.658	0.775
	(1.789)	(1.183)	(1.085)	(1.239)
any med. cond., children	0.349	0.276	0.267	0.277
# of med. cond., children	0.643	0.465	0.434	0.437
	(1.381)	(1.013)	(0.985)	(0.911)
hourly wage		8.89	8.65	14.20
		(5.05)	(4.23)	(7.70)
hours worked		24.0	40.8	41.4
		(7.4)	(5.9)	(5.0)
income as percentage of FPL	56.45	120.1	128.8	258.9
	(67.27)	(114.0)	(97.38)	(157.1)
med. OOP expend., mother	332.6	322.8	259.4	407.5
	(1142.9)	(1103.0)	(693.3)	(785.2)
med. OOP expend., children	163.7	199.1	173.7	338.5
	(1450.6)	(826.0)	(1030.3)	(933.4)
Medicaid coverage, mother	0.711	0.456	0.440	0.0486
Medicaid coverage, children	0.858	0.711	0.712	0.240

Note: No standard deviations shown for indicator variables.
Source: Medical Expenditure Panel Survey, 1996 to 2008.

Table 5: **Reasons for Not Working**

	frequency	percent
could not find work	293	18.0
retired	12	0.74
unable to work because ill/disabled	507	31.1
on temporary layoff	5	0.31
maternity leave	41	2.51
going to school	93	5.70
taking care of home or family	607	37.2
wanted some time off	10	0.61
waiting to start new job	13	0.80
other	50	3.07
total	1,631	100

Notes: reasons for not working given by individuals in employment state non-work.
Source: Medical Expenditure Panel Survey, 1996 to 2008.

Table 6: **Means and Standard Deviations (in Parentheses) of State-Level Variables**

	mean	std.dev.
state unemployment rate	5.199	(1.017)
state minimum wage	5.482	(0.797)
fractions of firms offering ESHI	0.556	(0.0541)
employer ESHI cost per hour	3.106	(0.849)
employee annual ESHI premium	2,175.1	(718.0)
annual federal poverty line	14,818.4	(3,315.7)
Medicaid eligibility threshold, parents	999.1	(648.5)
Medicaid eligibility threshold, children 0 to 1	2,359.4	(674.3)
Medicaid eligibility threshold, children 1 to 5	1,897.7	(663.8)
Medicaid eligibility threshold, children 6 to 14	1,590.7	(714.7)
Medicaid eligibility threshold, children 15 to 16	1,508.6	(792.8)
Medicaid eligibility threshold, children 17	1,505.8	(794.8)
Medicaid eligibility threshold, children 18 to 19	1,502.6	(797.0)
Medicaid eligibility threshold under PPACA	1,704.1	(381.3)
observations	10,278	

Note: means and standard deviations (in parentheses) of state-level variables weighted by number of individual observations per state and year.
Sources: see Appendix B.

Table 7: **Means of Simulated Medicaid Eligibility by Demographic Cell**

	parental Medicaid			children's Medicaid		
	white	black	Hispanic	white	black	Hispanic
age 18-24	0.783	0.813	0.791	0.921	0.937	0.919
age 25-34						
no high school	0.818	0.891	0.832	0.919	0.961	0.932
high school	0.646	0.688	0.681	0.792	0.816	0.817
college	0.458	0.454	0.479	0.543	0.542	0.570
age 35-44						
no high school	0.784	0.848	0.757	0.883	0.922	0.872
high school	0.579	0.605	0.654	0.687	0.711	0.781
college	0.445	0.424	0.546	0.498	0.490	0.640
age 45-55						
no high school	0.800	0.790	0.801	0.866	0.855	0.886
high school	0.554	0.626	0.603	0.642	0.723	0.702
college	0.431	0.480	0.559	0.478	0.519	0.636

Notes: each cell contains the mean of simulated Medicaid eligibility for parents and children over years and states (eligibility simulated based on national sample of single mothers (see text for details).
Source: Medical Expenditure Panel Survey, 1996 to 2007, author's calculations.

Table 8: **Means of Simulated Medicaid Eligibility by Year**

	parental Medicaid	children's Medicaid
1996	0.411	0.533
1997	0.509	0.609
1998	0.614	0.696
1999	0.648	0.740
2001	0.702	0.791
2002	0.705	0.798
2003	0.706	0.796
2004	0.708	0.798
2005	0.714	0.803
2006	0.716	0.812
2007	0.724	0.817

Notes: each cell contains the mean of simulated Medicaid eligibility for parents and children over demographic cells and states (eligibility simulated based on national sample of single mothers; see text for details).
Source: Medical Expenditure Panel Survey, 1996 to 2007 and author's calculations.

Table 9a: **Reduced Form-Results: OLS Regressions of Employment Choices on Simulated Medicaid Eligibility for Parents**

	(1) non-work	(2) part-time	(3) full-time, no ESHI	(4) full-time, ESHI
simulated Medicaid	0.139***	0.011	0.025	-0.172***
eligibility, mother	(0.031)	(0.021)	(0.024)	(0.038)
number of children	0.141***	-0.020*	-0.029*	-0.090***
aged 0 to 2	(0.012)	(0.011)	(0.015)	(0.013)
number of children	0.075***	0.007	0.003	-0.084***
aged 3 to 4	(0.014)	(0.010)	(0.010)	(0.013)
number of children	0.047***	-0.001	0.009	-0.053***
aged 5 to 10	(0.011)	(0.005)	(0.008)	(0.007)
number of children	0.022**	0.002	0.026***	-0.046***
aged 11 or older	(0.008)	(0.006)	(0.006)	(0.009)
any medical condition -	-0.010	0.008	0.007	-0.007
mother	(0.014)	(0.014)	(0.010)	(0.015)
number of medical	0.065***	-0.013***	-0.021***	-0.026***
conditions - mother	(0.005)	(0.005)	(0.004)	(0.005)
any medical condition -	0.026*	-0.014	-0.003	-0.006
children	(0.015)	(0.015)	(0.013)	(0.018)
number of medical	-0.004	0.002	-0.000	-0.001
conditions - children	(0.006)	(0.006)	(0.005)	(0.006)
state unemployment rate	0.025**	-0.007	-0.005	-0.018*
	(0.010)	(0.008)	(0.008)	(0.009)
minimum wage	-0.003	0.010	0.016	-0.015
	(0.015)	(0.009)	(0.011)	(0.012)
hourly ESHI premium paid	0.002	0.048*	-0.015	-0.038
by employer	(0.026)	(0.025)	(0.026)	(0.025)
hourly ESHI premium paid	0.027	-0.058	0.072*	-0.045
by employee	(0.041)	(0.038)	(0.041)	(0.045)
fraction of firms offering	0.054	-0.203	0.101	-0.070
ESHI	(0.206)	(0.136)	(0.159)	(0.203)
constant	0.879***	0.487***	0.091	-0.343**
	(0.179)	(0.142)	(0.172)	(0.161)
observations	11,411	11,411	11,411	11,411

Notes: Medicaid eligibility simulated based on national sample of single mothers (see text for details); age, age squared, black, Hispanic, education, and state and year fixed effects included; standard errors clustered at state-level in parentheses; * p<0.1, ** p<0.05, *** p<0.01.
Source: Medical Expenditure Panel Survey, 1996 to 2008, author’s calculations.

Table 9b: **Reduced-Form Results: OLS Regressions of Employment Choices on Simulated Medicaid Eligibility for Parents and Children**

	(1) non-work	(2) part-time	(3) full-time, no ESHI	(4) full-time, ESHI
simulated Medicaid	0.065	-0.050	-0.063	0.065
eligibility, mothers	(0.064)	(0.051)	(0.047)	(0.062)
simulated Medicaid	0.092	0.076	0.109**	-0.294***
eligibility, children	(0.063)	(0.058)	(0.043)	(0.059)
number of children	0.141***	-0.020*	-0.029*	-0.090***
aged 0 to 2	(0.012)	(0.011)	(0.015)	(0.013)
number of children	0.075***	0.007	0.003	-0.083***
aged 3 to 4	(0.014)	(0.010)	(0.010)	(0.013)
number of children	0.047***	-0.001	0.009	-0.053***
aged 5 to 10	(0.011)	(0.005)	(0.008)	(0.007)
number of children	0.021**	0.002	0.026***	-0.046***
aged 11 or older	(0.008)	(0.006)	(0.006)	(0.009)
any medical condition -	-0.010	0.008	0.008	-0.007
mothers	(0.014)	(0.014)	(0.010)	(0.015)
number of medical	0.065***	-0.014***	-0.021***	-0.026***
conditions - mothers	(0.005)	(0.005)	(0.004)	(0.005)
any medical condition -	0.026*	-0.015	-0.003	-0.005
children	(0.015)	(0.015)	(0.013)	(0.018)
number of medical	-0.004	0.003	0.000	-0.001
conditions – children	(0.006)	(0.006)	(0.005)	(0.006)
state unemployment rate	0.025**	-0.007	-0.005	-0.016*
	(0.010)	(0.008)	(0.008)	(0.009)
minimum wage	-0.002	0.011	0.019*	-0.021*
	(0.015)	(0.010)	(0.010)	(0.011)
hourly ESHI premium paid	0.007	0.052**	-0.010	-0.053**
by employer	(0.026)	(0.025)	(0.026)	(0.026)
hourly ESHI premium paid	0.029	-0.057	0.074*	-0.050
by employee	(0.040)	(0.038)	(0.041)	(0.043)
fraction of firms offering	0.067	-0.192	0.116	-0.111
ESHI	(0.207)	(0.137)	(0.158)	(0.193)
constant	0.787***	0.412**	-0.019	-0.049
	(0.190)	(0.167)	(0.169)	(0.147)
observations	11,411	11,411	11,411	11,411

Notes: Medicaid eligibility simulated based on national sample of single mothers (see text for details); age, age squared, black, Hispanic, education, and state and year fixed effects included; standard errors clustered at state-level in parentheses; * p<0.1, ** p<0.05, *** p<0.01.
Source: Medical Expenditure Panel Survey, 1996 to 2008, author's calculations.

Table 10: **OLS Regression of Log-Wage**

	ln(wage)	
log of hourly ESHI cost	-1.000	(.)
years of education	0.128***	(0.008)
black	-0.040	(0.032)
Hispanic	-0.145***	(0.032)
age	0.067***	(0.013)
age squared/100	-0.054***	(0.017)
any medical condition, mothers	0.099***	(0.035)
number of medical conditions, mothers	0.006	(0.015)
state unemployment rate	0.014	(0.011)
minimum wage	-0.033	(0.021)
mean any med. cond., mother	-0.194***	(0.045)
mean # of med. cond., mother	0.056***	(0.014)
mean unemployment rate	0.002	(0.028)
mean minimum wage	0.219***	(0.027)
mean # of children 0 to 2	-0.183***	(0.043)
mean # of children 3 to 4	-0.053	(0.040)
mean # of children 5 to 10	-0.074**	(0.029)
mean # of children 11+	-0.017	(0.027)
mean any med. cond., children	-0.051**	(0.024)
mean # of med. cond., children	0.014	(0.010)
mean parental Medicaid eligibility threshold	-0.000	(0.000)
mean Medicaid eligibility threshold, children 0 to 1	-0.000	(0.000)
mean Medicaid eligibility threshold, children 1 to 5	0.000	(0.000)
mean Medicaid eligibility threshold, children 6 to 14	-0.000	(0.000)
mean Medicaid eligibility threshold, children 15 and older	0.000	(0.000)
mean hourly ESHI cost, employee	0.102**	(0.042)
mean fraction of firms offering ESHI	0.439**	(0.210)
$\lambda^{10,L}$ x (ESHI=0)	-0.075	(0.103)
$\lambda^{10,S}$ x (ESHI=0)	0.987***	(0.038)
$\lambda^{11,L}$ x (ESHI=1)	-0.421***	(0.114)
$\lambda^{11,S}$ x (ESHI=1)	0.993***	(0.087)
$\lambda^{10,L}$x (ESHI=0) x (t=2)	-0.014	(0.039)
$\lambda^{10,S}$ x (ESHI=0) x (t=2)	-0.050***	(0.016)
$\lambda^{11,L}$ x (ESHI=1) x (t=2)	0.175***	(0.066)
$\lambda^{11,S}$ x (ESHI=1) x (t=2)	-0.041	(0.050)
constant	-1.396***	(0.274)
observations	7,097	

Notes: pooled OLS regression of log-wage for both time periods; estimated on sample with observed wage (LFP=1); standard errors clustered at state level in parentheses; see text for definition of selection correction terms (λs); * p<0.1, ** p<0.05, *** p<0.01.
Source: Medical Expenditure Panel Survey, 1996 to 2008, author's calculations.

Table 11: **Means and Standard Deviations (in Parentheses) of Simulated Outcomes by Employment Choice Under Different Health Insurance Policies**

	non-work	part-time	full-time, no ESHI	full-time, ESHI
(a) independent of Medicaid rules				
hourly wage	0	8.993	8.998	12.71
	(0)	(3.247)	(3.161)	(5.687)
hours worked per week/40	0	0.516	1.004	1.011
	(0)	(0.0831)	(0.0658)	(0.0739)
monthly earnings	0	805.8	1567.3	2239.0
	(0)	(345.6)	(567.1)	(1083.3)
monthly transfers	745.5	666.1	353.1	89.83
	(250.9)	(257.4)	(337.8)	(425.6)
(b) current Medicaid rules				
health insurance, mothers	1	0.860	0.595	1
	(0)	(0.347)	(0.491)	(0)
health insurance, children	1	0.969	0.751	1
	(0)	(0.170)	(0.424)	(0)
out-of-pocket medical	180.2	169.7	190.4	702.2
expenditure, mothers	(651.0)	(476.4)	(360.3)	(808.5)
out-of-pocket medical	95.86	88.43	103.7	526.1
expenditure, children	(809.5)	(366.7)	(489.2)	(1390.0)
monthly per-capita consumption	0.264	0.509	0.653	0.704
(in 1,000 1996 $)	(0.0700)	(0.0906)	(0.104)	(0.284)
(c) PPACA – Medicaid expansion only				
health insurance, mothers	1	0.992	0.834	1
	(0)	(0.0900)	(0.372)	(0)
health insurance, children	1	0.993	0.862	1
	(0)	(0.0834)	(0.344)	(0)
out-of-pocket medical	121.0	122.0	143.8	864.2
expenditure, mothers	(146.2)	(147.9)	(185.2)	(748.1)
out-of-pocket medical	107.8	108.2	114.1	617.4
expenditure, children	(314.3)	(314.4)	(316.1)	(1301.0)
monthly per-capita consumption	0.265	0.510	0.654	0.696
(in 1,000 1996 $)	(0.0669)	(0.0904)	(0.104)	(0.281)
(d) PPACA – Medicaid expansion and subsidies				
health insurance, mothers	1	1.000	0.997	1
	(0)	(0.0221)	(0.0530)	(0)
health insurance, children	1	1.000	0.997	1
	(0)	(0.0221)	(0.0530)	(0)
out-of-pocket medical	121.0	147.0	463.5	864.2
expenditure, mothers	(146.2)	(435.2)	(756.7)	(748.1)
out-of-pocket medical	107.8	130.8	282.3	617.4
expenditure, children	(314.3)	(1227.7)	(531.1)	(1301.0)
monthly per-capita consumption	0.265	0.489	0.370	0.696
(in 1,000 1996 $)	(0.0669)	(0.106)	(0.306)	(0.281)

Note: predicted outcomes by employment alternative based on wage and medical expenditure regressions and different health insurance policies (current Medicaid policies, Patient Protection and Affordable Care Act [PPACA] Medicaid expansions, and PPACA Medicaid expansions and health insurance subsidies); means and standard deviations (in parentheses) shown.
Source: Medical Expenditure Panel Survey, 1996 to 2008, and author's calculations.

Table 12: **Two-Part Regressions of Out-of-Pocket Medical Expenditure Regressions for Mothers and Children**

	mothers' expenditure		children's expenditure	
	1(E>0)	ln(E)IE>0	1(E>0)	ln(E)IE>0
predicted ESHI	0.712***	1.193**	0.745***	1.140***
	(0.273)	(0.478)	(0.213)	(0.353)
parental Medicaid	-0.420***	-0.458***		
	(0.041)	(0.041)		
children's Medicaid			-0.246***	-0.277***
			(0.018)	(0.019)
years of education	0.028**	0.017	0.037***	0.055***
	(0.014)	(0.020)	(0.011)	(0.017)
black	-0.256***	-0.554***	-0.498***	-0.645***
	(0.041)	(0.047)	(0.032)	(0.057)
Hispanic	-0.159***	-0.191**	-0.138**	-0.244***
	(0.051)	(0.072)	(0.056)	(0.074)
age	-0.072***	0.008		
	(0.015)	(0.027)		
age squared/100	0.101***	0.016		
	(0.020)	(0.031)		
number of children aged 0 to 2			0.453***	0.385***
			(0.098)	(0.110)
number of children aged 3 to 4			0.413***	0.397***
			(0.097)	(0.106)
number of children aged 5 to 10			0.431***	0.461***
			(0.072)	(0.095)
number of children aged 11 or older			0.428***	0.470***
			(0.067)	(0.098)
any medical condition	0.062	-0.085		
	(0.124)	(0.112)		
number of medical conditions	0.152**	0.177***		
	(0.062)	(0.056)		
any medical condition - children			0.162	-0.047
			(0.099)	(0.141)
number of medical conditions - children			0.017	0.107
			(0.058)	(0.099)
mean # of children 0 to 2			-0.097	-0.231
			(0.104)	(0.141)
mean # of children 3 to 4			-0.030	-0.227*
			(0.106)	(0.134)
mean # of children 5 to 10			-0.108	-0.210*
			(0.080)	(0.112)
mean # of children 11+			-0.081	-0.016
			(0.076)	(0.110)
mean any med. cond., mother	0.266**	0.196*		
	(0.128)	(0.104)		
mean # of med. cond., mother	0.129**	0.035		
	(0.060)	(0.051)		
mean any med. cond., children			0.195*	0.257*
			(0.109)	(0.143)
mean # of med. cond., children			0.101	0.013
			(0.072)	(0.101)
constant	1.303***	3.708***	-0.671***	2.826***
	(0.298)	(0.481)	(0.083)	(0.159)
observations	10,278	7,797	10,278	6,799
R^2		0.158		0.144

Notes: separate two-part regressions of mothers' annual out-of-pocket medical expenditure and sum of children's annual out-of-pocket medical expenditure (first part: logit of positive expenditure, second part: OLS of log-expenditure for positive expenditure); standard errors clustered at state level in parentheses; * p<0.1, ** p<0.05, *** p<0.01.
Source: Medical Expenditure Panel Survey, 1996 to 2008, author's calculations.

Table 13: **Multinomial Logit of Employment Choice**

random preference parameters			
	hours	HI, mother	HI, children
age	0.031**	0.102***	
	(0.013)	(0.016)	
black	-0.796***	-0.935***	0.950**
	(0.221)	(0.297)	(0.451)
Hispanic	-1.655***	0.067	-1.448***
	(0.240)	(0.405)	(0.558)
number of kids under 4	-1.386***		
	(0.140)		
number of conditions, mother		0.385***	
		(0.088)	
age of youngest child			0.057
			(0.038)
number of conditions, children			0.265
			(0.185)
mean of preference shocks	-16.975***	-2.775**	0.871
	(1.316)	(1.204)	(1.315)
	variance of preference shocks		
hours	5.536***		
	(0.182)		
HI, mother	2.509***	3.101***	
	(0.282)	(0.286)	
HI, children	-0.108	-1.844***	4.058***
	(0.373)	(0.651)	(0.382)
fixed preference parameters			
consumption		1.000	
		(.)	
consumption squared		6.030***	
		(0.418)	
hours squared		11.416***	
		(0.737)	
consumption x hours		4.452***	
		(0.873)	
consumption x HI mother		2.173	
		(1.784)	
consumption x HI children		-16.690***	
		(1.898)	
hours x HI mother		-3.828***	
		(0.707)	
hours x HI children		10.225***	
		(1.129)	
HI mother x HI children		2.165***	
		(0.743)	
gamma part-time		4.035***	
		(0.158)	

Notes: the first panel shows estimates of the effects of observables on preference parameters and estimates of the means and variance-covariance matrix of the unobserved preference component; the second panel shows estimates of the fixed preference parameters (see equations (#) and (#) in the text for the functional form of utility function and preference parameters); bootstrapped standard errors clustered at state level in parentheses; * p<0.1, ** p<0.05, *** p<0.01.
Source: Medical Expenditure Panel Survey, 1996 to 2008, author's calculations.

Table 14: **Marginal Effects and Their Standard Errors Based on Multinomial Logit Estimates**

	non-work	part-time	full-time, no ESHI	full-time, ESHI
age	-0.000631	-0.000242	-0.00146	0.00233
	(0.0000161)	(0.0000174)	(0.0000303)	(0.0000176)
black	0.0398	0.00481	-0.0117	-0.0329
	(0.000142)	(0.000161)	(0.000233)	(0.000156)
Hispanic	0.0921	0.00264	-0.0281	-0.0666
	(0.000235)	(0.000206)	(0.000386)	(0.000270)
# of children under 4	0.0839	0.00179	-0.0370	-0.0487
	(0.000161)	(0.000123)	(0.000168)	(0.000157)
# of med. cond., mother	0.00431	-0.000499	-0.00842	0.00461
	(0.0000627)	(0.0000677)	(0.000115)	(0.0000623)
age of youngest child	0.000252	0.0000595	-0.000688	0.000376
	(0.00000488)	(0.00000591)	(0.0000128)	(0.00000690)
# of med. cond., children	0.00116	0.000271	-0.00317	0.00173
	(0.0000226)	(0.0000275)	(0.0000589)	(0.0000319)
observations	10,278	10,278	10,278	10,278

Note: Marginal effects based on the multinomial Logit estimates in Table 12 calculated using a discrete change in the respective variables; standard errors in parentheses.
Source: Medical Expenditure Panel Survey, 1996 to 2008, and author's calculations.

Table 15: **Observed and Simulated Employment Choices Under Different Health Insurance Policies (Mean Fractions and Confidence Intervals)**

	observed	actual Medicaid rules	PPACA Medicaid expansions only	PPACA Medicaid expansions and subsidies
non-work	0.309	0.311	0.326	0.293
	[0.298,0.321]	[0.309,0.314]	[0.323,0.328]	[0.289,0.296]
part-time	0.161	0.148	0.148	0.126
	[0.152,0.170]	[0.146,0.150]	[0.146,0.150]	[0.123,0.129]
full-time, no ESHI	0.199	0.212	0.218	0.380
	[0.190,0.209]	[0.209,0.215]	[0.215,0.221]	[0.373,0.387]
full-time, ESHI	0.331	0.329	0.308	0.202
	[0.318,0.343]	[0.324,0.333]	[0.304,0.313]	[0.197,0.207]
observations	10,278	10,278,000	10,278,000	10,278,000

Notes: fractions of single mothers in each employment alternative, observed and simulated under different policies; simulations using 1,000 draws for every individual in sample; 95 percent confidence intervals based on standard errors clustered at individual level in brackets.
Source: Medical Expenditure Panel Survey, 1996 to 2008, author’s calculations.

Table 16: **Observed and Simulated Employment Choices for Various Subsamples (Mean Fractions and Confidence Intervals)**

	observed	actual Medicaid rules	PPACA Medicaid expansions only	PPACA Medicaid expansions and subsidies
		(a.1) children aged 0 to 4		
non-work	0.402	0.388	0.409	0.388
	[0.381,0.422]	[0.384,0.393]	[0.405,0.414]	[0.383,0.393]
part-time	0.181	0.164	0.167	0.154
	[0.165,0.197]	[0.160,0.168]	[0.163,0.170]	[0.149,0.159]
full-time, no ESHI	0.219	0.200	0.191	0.275
	[0.202,0.235]	[0.195,0.204]	[0.187,0.196]	[0.266,0.284]
full-time, ESHI	0.199	0.248	0.233	0.183
	[0.181,0.216]	[0.243,0.253]	[0.227,0.238]	[0.177,0.189]
observations	3,239	3,239,000	3,239,000	3,239,000
		(a.2) no children aged 0 to 4		
non-work	0.267	0.276	0.287	0.249
	[0.254,0.280]	[0.273,0.279]	[0.284,0.290]	[0.246,0.252]
part-time	0.151	0.141	0.139	0.113
	[0.140,0.162]	[0.138,0.144]	[0.136,0.142]	[0.109,0.117]
full-time, no ESHI	0.191	0.218	0.231	0.428
	[0.179,0.202]	[0.214,0.222]	[0.227,0.235]	[0.420,0.436]
full-time, ESHI	0.391	0.366	0.343	0.210
	[0.376,0.406]	[0.360,0.371]	[0.337,0.349]	[0.204,0.217]
observations	7,039	7,039,000	7,039,000	7,039,000
		(b.1) mother has medical conditions		
non-work	0.368	0.307	0.315	0.274
	[0.350,0.386]	[0.303,0.311]	[0.311,0.319]	[0.270,0.279]
part-time	0.143	0.139	0.140	0.113
	[0.131,0.156]	[0.136,0.143]	[0.137,0.143]	[0.108,0.117]
full-time, no ESHI	0.176	0.201	0.215	0.418
	[0.162,0.189]	[0.197,0.206]	[0.211,0.220]	[0.408,0.428]
full-time, ESHI	0.313	0.352	0.329	0.195
	[0.295,0.331]	[0.345,0.359]	[0.323,0.336]	[0.188,0.203]
observations	4,589	4,589,000	4,589,000	4,589,000
		(b.2) mother has no medical conditions		
non-work	0.262	0.315	0.334	0.307
	[0.248,0.277]	[0.311,0.319]	[0.330,0.338]	[0.303,0.312]
part-time	0.175	0.155	0.154	0.136
	[0.162,0.187]	[0.152,0.158]	[0.151,0.158]	[0.132,0.140]
full-time, no ESHI	0.218	0.220	0.221	0.349
	[0.205,0.232]	[0.216,0.225]	[0.217,0.225]	[0.341,0.358]
full-time, ESHI	0.345	0.310	0.291	0.207
	[0.329,0.361]	[0.304,0.315]	[0.285,0.297]	[0.200,0.213]
observations	5,689	5,689,000	5,689,000	5,689,000

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	observed	actual Medicaid rules	PPACA Medicaid expansions only	PPACA Medicaid expansions and subsidies
		(c.1) children have medical conditions		
non-work	0.364	0.313	0.324	0.291
	[0.342,0.385]	[0.308,0.318]	[0.319,0.329]	[0.286,0.297]
part-time	0.149	0.145	0.146	0.125
	[0.134,0.165]	[0.141,0.149]	[0.142,0.150]	[0.120,0.130]
full-time, no ESHI	0.179	0.202	0.213	0.373
	[0.163,0.196]	[0.197,0.208]	[0.207,0.218]	[0.361,0.385]
full-time, ESHI	0.308	0.340	0.317	0.211
	[0.287,0.329]	[0.332,0.348]	[0.309,0.325]	[0.202,0.220]
observations	3,056	3,056,000	3,056,000	3,056,000
		(c.2) children have no medical conditions		
non-work	0.287	0.311	0.326	0.293
	[0.273,0.300]	[0.307,0.314]	[0.323,0.330]	[0.289,0.297]
part-time	0.165	0.149	0.149	0.126
	[0.155,0.176]	[0.146,0.152]	[0.146,0.152]	[0.122,0.130]
full-time, no ESHI	0.208	0.216	0.221	0.383
	[0.196,0.219]	[0.212,0.220]	[0.217,0.224]	[0.375,0.391]
full-time, ESHI	0.340	0.324	0.304	0.198
	[0.326,0.355]	[0.319,0.329]	[0.299,0.310]	[0.192,0.204]
observations	7,222	7,222,000	7,222,000	7,222,000
		(d.1) income is below median		
non-work	0.537	0.339	0.355	0.330
	[0.521,0.554]	[0.335,0.343]	[0.352,0.359]	[0.326,0.334]
part-time	0.199	0.165	0.168	0.148
	[0.186,0.212]	[0.162,0.168]	[0.165,0.171]	[0.144,0.151]
full-time, no ESHI	0.201	0.211	0.215	0.337
	[0.188,0.214]	[0.207,0.214]	[0.212,0.218]	[0.329,0.345]
full-time, ESHI	0.063	0.285	0.262	0.186
	[0.055,0.071]	[0.281,0.289]	[0.259,0.266]	[0.182,0.190]
observations	5,139	5,139,000	5,139,000	5,139,000
		(d.2) income is above median		
non-work	0.082	0.284	0.296	0.255
	[0.074,0.090]	[0.280,0.288]	[0.292,0.300]	[0.251,0.259]
part-time	0.122	0.131	0.128	0.104
	[0.111,0.134]	[0.127,0.134]	[0.125,0.132]	[0.099,0.108]
full-time, no ESHI	0.198	0.213	0.222	0.423
	[0.185,0.211]	[0.208,0.218]	[0.217,0.227]	[0.414,0.433]
full-time, ESHI	0.598	0.372	0.354	0.218
	[0.581,0.615]	[0.365,0.380]	[0.346,0.362]	[0.209,0.227]
observations	5,139	5,139,000	5,139,000	5,139,000

Notes: fractions of single mothers in each employment alternative, observed and simulated under different policies and for indicated subsamples; 95 percent confidence intervals based on standard errors clustered at individual level in brackets.
Source: Medical Expenditure Panel Survey, 1996 to 2008, author’s calculations.

Table 17: **Percent of Single Mothers Changing Employment Status**

	non-work	part-time	full-time, no ESHI	full-time, ESHI
(a) policy changes from current Medicaid rules to PPACA Medicaid expansions only				
non-work	97.38	1.58	0.97	0.35
part-time	6.32	87.16	4.93	1.56
full-time, no ESHI	6.14	3.83	85.39	4.47
full-time, ESHI	0.23	1.81	8.10	89.70
(b) policy changes from current Medicaid rules to PPACA Medicaid expansions and health insurance subsidies				
non-work	85.87	2.27	11.97	0.15
part-time	6.12	68.53	24.60	1.00
full-time, no ESHI	7.78	4.84	82.56	4.81
full-time, ESHI	0.12	2.21	39.92	57.71

Notes: each cell contains the percent of single mothers switching employment from row alternatives (employment choice under current Medicaid rules) to column alternatives (under PPACA Medicaid expansions only).
Source: Medical Expenditure Panel Survey, 1996 to 2008, author's calculations.

Table 18: **Means and Standard Deviations (in Parentheses) of Annual Per-Family Government Expenditure Under Current Policies and PPACA and Compensating Variation**

	current policies	PPACA	difference
(a) policy costs			
Medicaid expenditure	3,706.48	3,554.98	-151.50
	(3,312.72)	(3,452.82)	(2,424.56)
HI subsidy expenditure	0.00	2,109.55	2,109.55
	(0.00)	(3,914.50)	(3,914.50)
transfers	5,480.84	5,345.47	-135.38
	(6,919.54)	(6,553.64)	(3,417.35)
total expenditure	9,187.32	11,010.00	1,822.67
	(9,495.32)	(8,254.44)	(5,105.03)
(b) individual welfare consequences			
compensating variation			-6,441.70
			(5,599.04)

Notes: average per-family government expenditure based on simulated employment choice under current Medicaid policies (column 1), PPACA Medicaid expansions and health insurance subsidies (column 2), and difference between column 2 and column 1 (column 3). Transfers consist of welfare, food stamps, EITC, and income and payroll taxes. Compensating variation is the amount of money paid to families under PPACA to equate utilities under both policy regimes. All values are in 2008 dollars.

Table A1: **Bivariate Probit of Labor Force Participation (LFP) and Employer-Sponsored Health Insurance (ESHI)**

	(1)	(2)	(3)	(4)
	year 1		year 2	
	LFP=1	ESHI=1	LFP=1	ESHI=1
years of education	0.104***	0.109***	0.114***	0.110***
	(0.007)	(0.020)	(0.009)	(0.017)
black	-0.209***	-0.022	-0.268***	0.014
	(0.050)	(0.066)	(0.061)	(0.073)
Hispanic	-0.165*	-0.146**	-0.140	-0.123*
	(0.089)	(0.060)	(0.113)	(0.072)
age	0.093***	0.104***	0.075***	0.104***
	(0.018)	(0.026)	(0.023)	(0.023)
age squared/100	-0.128***	-0.100***	-0.105***	-0.105***
	(0.026)	(0.034)	(0.031)	(0.029)
any medical condition, mother	-0.119	0.032	0.103	0.180
	(0.176)	(0.157)	(0.154)	(0.209)
number of medical conditions, mother	-0.138*	-0.062	0.013	0.086
	(0.078)	(0.104)	(0.079)	(0.121)
any medical condition, children	0.202	0.076	-0.381**	-0.022
	(0.155)	(0.223)	(0.192)	(0.181)
number of medical conditions, children	-0.002	0.036	0.126	0.016
	(0.095)	(0.095)	(0.093)	(0.109)
number of children aged 0 to 2	-0.216		-0.479**	
	(0.186)		(0.224)	
number of children aged 3 to 4	-0.290		-0.385*	
	(0.200)		(0.225)	
number of children aged 5 to 10	-0.277*		-0.273	
	(0.168)		(0.207)	
number of children aged 11 or older	-0.276		-0.106	
	(0.181)		(0.194)	
hourly ESHI premium paid		-0.336		0.409
by employee		(0.350)		(0.338)
fraction of firms offering ESHI		-0.732		-1.897
		(1.851)		(1.176)
parental Medicaid eligibility threshold	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Medicaid eligibility threshold,	0.000	-0.000	-0.000	0.000
children 0 to 1	(0.000)	(0.000)	(0.000)	(0.000)
Medicaid eligibility threshold,	-0.000	-0.000	-0.000	0.000
children 1 to 5	(0.000)	(0.000)	(0.000)	(0.000)
Medicaid eligibility threshold,	0.000	0.001	0.000	-0.000
children 6 to 14	(0.000)	(0.000)	(0.000)	(0.000)
Medicaid eligibility threshold,	-0.000	-0.000	-0.000	0.000
children 15 and older	(0.000)	(0.000)	(0.000)	(0.000)
mean any med. cond., mother	0.161	-0.115	-0.172	-0.346
	(0.170)	(0.165)	(0.179)	(0.229)
mean # of med. cond., mother	-0.078	0.107	-0.202**	-0.027
	(0.072)	(0.101)	(0.086)	(0.131)
mean any med. cond., children	-0.285**	-0.070	0.271	0.210
	(0.139)	(0.219)	(0.202)	(0.205)

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	(1)	(2)	(3)	(4)
	year 1		year 2	
	LFP=1	ESHI=1	LFP=1	ESHI=1
mean # of med. cond., children	-0.008	-0.052	-0.142	-0.083
	(0.084)	(0.093)	(0.116)	(0.121)
mean # of children 0 to 2	-0.316		0.056	
	(0.192)		(0.228)	
mean # of children 3 to 4	0.008		0.082	
	(0.213)		(0.223)	
mean # of children 5 to 10	0.099		0.067	
	(0.195)		(0.192)	
mean # of children 11+	0.184		0.019	
	(0.189)		(0.192)	
mean hourly ESHI cost, employee		0.200		-0.523
		(0.361)		(0.348)
mean fraction of firms offering		1.147		2.972**
ESHI		(1.839)		(1.220)
mean parental Medicaid eligibility	-0.000	0.000	-0.000	-0.000
threshold	(0.000)	(0.000)	(0.000)	(0.000)
mean Medicaid eligibility	-0.000	0.000	0.000	-0.000
threshold, children 0 to 1	(0.000)	(0.000)	(0.000)	(0.000)
mean Medicaid eligibility	0.000	0.000	0.000	-0.000
threshold, children 1 to 5	(0.000)	(0.000)	(0.000)	(0.000)
mean Medicaid eligibility	-0.000	-0.001	-0.000	0.000
threshold, children 6 to 14	(0.000)	(0.000)	(0.000)	(0.000)
mean Medicaid eligibility	0.000	0.000	-0.000	-0.000
threshold, children 15 and older	(0.000)	(0.000)	(0.000)	(0.000)
constant	-1.761***	-3.178***	-1.536***	-3.430***
	(0.329)	(0.722)	(0.421)	(0.605)
observations	5,139		5,139	
rho	-0.359		-0.353	

Notes: bivariate probit with incomplete observability, where ESHI is only observed if LFP=1; estimated separately for each time period (year 1 and year 2); standard errors clustered at state level in parentheses; * p<0.1, ** p<0.05, *** p<0.01.
Source: Medical Expenditure Panel Survey, 1996 to 2008, author's calculations.

Table A2: **Observed and Simulated Employment Choices Under Different Health Insurance Policies (Mean Fractions and Confidence Intervals) With Unrestricted Compensating Wage Differential**

	observed	actual Medicaid rules	PPACA Medicaid expansions only	PPACA Medicaid expansions and subsidies
non-work	0.309	0.310	0.323	0.220
	[0.298,0.321]	[0.307,0.313]	[0.320,0.327]	[0.215,0.225]
part-time	0.161	0.150	0.149	0.106
	[0.152,0.170]	[0.147,0.153]	[0.146,0.152]	[0.103,0.110]
full-time, no ESHI	0.199	0.203	0.203	0.485
	[0.190,0.209]	[0.199,0.206]	[0.200,0.207]	[0.475,0.495]
full-time, ESHI	0.331	0.338	0.324	0.189
	[0.318,0.343]	[0.332,0.343]	[0.319,0.330]	[0.183,0.194]
observations	10,278	10,278,000	10,278,000	10,278,000

Notes: fractions of single mothers in each employment alternative, observed and simulated under different policies; simulations using 1,000 draws for every individual in sample; confidence intervals based on standard errors clustered at individual level in brackets. In contrast to Table 14, this table is based on estimates from the two-step procedure when the compensating wage differential parameter γ^S is unrestricted in the log-wage regression.

Source: Medical Expenditure Panel Survey, 1996 to 2008, author's calculations.