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Abstract

This study aims to determine the effect of the Massachusetts Health Care Reform on household health care expenditures. I follow the consumer choice theoretical framework, which says that a change in the price of health care will cause households to adjust their consumption choices based on their preferences. Using data from the Consumer Expenditure Survey, I apply a difference-in-difference technique to isolate the effect of the reform on spending on health care, prescription drugs, and health insurance as a share of total household expenditures. The results are not statistically significant. However, using a difference-in-difference-in-differences estimation to determine the effect of the reform specifically on minorities, I find positive and significant results, which suggests that minorities spent a higher share of their budget on health after the reform. These findings require additional research to better understand how health care reform can affect household spending on health care.

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I. Introduction

Over the last two decades the United States has experienced dramatic increases in health care expenditures. Simultaneously, we have also seen a widening gap in access to care as well as disparities in quality of care. While generally acknowledged as a rising problem, states had done little to combat the problems until Massachusetts enacted a major health care reform law in 2006.

This paper aims to use the Massachusetts experiment to perform an empirical analysis of the effect of health care reform laws on health spending. This type of research is valuable to policymakers on both the state and federal level. Massachusetts served as the basis for the Affordable Care Act (ACA) and impacts within the state have the potential to predict the effects of the ACA. Understanding the specific ways the reform affected household expenditure patterns will also help improve future legislation. In this paper, I investigate the question: How did the Massachusetts Health Care Reform of 2006 affect household expenditures on health?

In Section II, I will summarize the Massachusetts Health Care Reform. Next, Section III provides a review of the literature surrounding the topic. Section IV provides the theoretical framework and Section V discusses the data and summary statistics. Section VI explains the empirical model I use in my analysis. I conclude in Section VII with a summary of my findings and recommendations for further research.

II. Background

The Massachusetts Health Care Reform, also known as Chapter 58, was passed in April of 2006 by the Massachusetts Legislature. The premise of the Reform was to improve access to health care and health insurance as well as decrease costs to individuals by restructuring both Massachusetts' Medicaid program (MassHealth) and the private insurance market and by creating two new health insurance programs: the subsidized CommonwealthCare (CommCare) and the unsubsidized CommonwealthChoice (CommChoice).

One of the main parts of Chapter 58 was the establishment of an individual mandate. This required all Massachusetts residents over the age of 18 to purchase credible health insurance, given there is an affordable plan available to them. Affordability was determined as a maximum amount an individual must pay for health insurance. The affordability schedule was progressive and set as a percentage of income, where those below 150 percent of the federal poverty line were considered not to be able to afford any plan and those above 500 percent of the federal poverty line were considered to be able to afford any plan. The credibility component of the mandate established the minimum creditable coverage a plan must offer. This included offering "comprehensive health benefits" including prescription drugs, no annual or per-sickness benefit maximums, no fee schedules for indemnity benefits, limits on deductibles, and maximums on in-network out-of-pocket spending. To ensure adherence to the individual mandate, Chapter 58

created penalties through state income taxes. In 2007, the penalty was $219 for an individual and in 2008 the maximum penalty was $912 for an individual (McDonough et al., 2008).

The reforms to MassHealth included expanding coverage eligibility and benefits available (dental care and glasses), particularly for children. Child eligibility for MassHealth was increased to 200-300 percent of the federal poverty line. To address the issue of the large number of eligible but not enrolled individuals, the Reform streamlined the application process, increased community outreach, and used the individual mandate. Previously, eligible but un-enrolled individuals relied heavily on hospital charity programs, however, the reform placed restrictions on the availability of reimbursements for hospitals. Physicians and hospitals also received higher payment rates for MassHealth care, conditional on pay-for-performance standards (McDonough et al., 2008).

Chapter 58 increased access to insurance and care for people that were ineligible for MassHealth but could not afford insurance in the private market by establishing CommonwealthCare. Uninsured adults under 150 percent of the federal poverty line were eligible for a health insurance plan with no premiums, no deductibles, and low copays. Those with incomes between 151 and 300 percent of the federal poverty line were eligible for plans with sliding-scale premiums and copays and no deductibles (McDonough et al., 2008).

CommonwealthChoice was created for individuals who were ineligible for CommCare but who did not have access to health insurance through an employer. These plans were available through the Connector but were private insurance plans.

The four different plans (Gold, Silver, Bronze, and Young Adult) varied in the amount of cost sharing between the insurer and individual (cost sharing increased as premiums decreased) (McDonough et al., 2008).

Chapter 58 also included reforms to regulations in the private insurance markets in Massachusetts. The main change was a merger of the small-group market and the individual market. This allowed individuals to purchase any of the plans that were available to small groups (employees in small firms). Lumping the groups together decreased the ratings and premiums for individual coverage but was expected to slightly increase the ratings and premiums for the small group coverage. Chapter 58 imposed new regulations on the private market including medical underwriting prohibition, pre-existing condition limitations, and guaranteed issue and renewal. Insurers were also required to cover dependent children until they turned 26 or for two years after they lost their dependent status (McDonough et al., 2008).

Private insurance market reforms were supplemented by new regulations on employers. Employers were required to make a "fair and reasonable" contribution to the health insurance costs of their employees. In addition, employers were required to allow all eligible full time employees to buy any of the health insurance plans offered by the employer and they were prohibited from paying a larger percentage of the premiums for higher paid employees. The Massachusetts Health Care Reform enabled previously uninsured and underinsured individuals to obtain health insurance and access to care. As of April 2008, 355,000 previously uninsured individuals gained health insurance coverage; 177,000 through CommCare, 55,000

through MassHealth, and 123,000 through private insurance (McDonough et al., 2008).

III. Literature Review

The Massachusetts Health Care Reform of 2006 has been studied extensively in the literature. However, most studies focus on the changes in insurance coverage, expected costs for health care, and changes in access to care. This paper takes an approach that combines the above research and examines the effect of the reform on actual consumer expenditures on health care.

The literature does not dispute that the number of insured individuals in Massachusetts has increased as a result of the reform and its mandate. Long et al. (2012) find that insurance coverage increased from 86.6% in 2006 to 94.2% in 2010. Of the newly insured individuals, approximately 25% enrolled in private insurance, 41% in CommCare, and 34% in Medicaid/MassHealth (Nardin et al., 2011). One of the largest drops in the uninsured population was amongst young adults who went from 21.1% uninsured in 2005-2006 to 8.2% in 2007-2008 (Long et al., 2010). Additionally, Long and Stockley (2010) find that despite the national recession, there was no significant change in the percentage insured in Massachusetts and instead only a slight shift in the type of coverage. They find that although most other states experienced an increase in the number of uninsured, Massachusetts saw a decrease in individuals with employer-sponsored insurance paired with a similar increase in individuals with public insurance.

Another focus of the literature surrounding insurance coverage is about the characteristics of the newly insured and still uninsured. One of the goals of the reform was to decrease insurance coverage disparities. Maxwell et al. (2011) find that the increase in coverage due to the reform among Hispanics was double that of the non-Hispanic white increase. Additionally, as of 2009, the individuals that were most likely to be uninsured were healthy young single males (Long and Stockley, 2010).

The literature is less clear about the expected costs for health care as a result of the reform. Decreasing costs as well as the financial burden of health care was a primary goal of the reform, however, the issue is complicated by the variety of different costs associated with health care. In terms of macro level health care costs, Miller (2012) as well as Long et al. (2012) find that the reform decreased emergency room usage (especially in non-emergency cases) in Massachusetts between 5 and 8% while emergency room usage was increasing on a national level.

Given the individual mandate, one health care expense for individuals is insurance premiums. Steinbrook (2008), and Hackmann et al. (2013) both find that due to the merger of the individual and small-group insurance markets, premiums for individuals have decreased. Hackmann et al. (2013) also find that after the reform, there were smaller mark-ups on individual coverage premiums by about $107 per person. However, according to Cogan et al. (2010), this decrease has come with possible consequences for the private insurance market including an increase in single-coverage employer sponsored insurance premiums by about 6% or, on average $262.

Another source of financial burden comes from out-of-pocket spending on health care. Long and Stockley (2010) and Steinbrook (2008) both find relative decreases in out-of-pocket spending within the first years of the reform in Massachusetts. Specifically, Long et al. (2012) find that in 2006, 9.8% of individuals had out-of-pocket spending that was greater than 10% of their income, however, by 2010, this had decreased to 6.1%. New enrollees in the subsidized CommCare saw their average monthly health care spending decrease from $518 pre-reform, to $454 in the phase in period, to $356 post-reform (Chandra et al., 2011). Additionally, out-of-pocket spending such as average annual hospital costs for insured individuals decreased by $124 (Hackmann et al., 2012).

Studies of the reform have also found evidence of the presence of adverse selection in the insurance market. Hackmann et al. (2012) finds that counties in Massachusetts that had greater increases in insurance coverage saw smaller increases in average cost per insured resident, implying that as the number of insured increased, average costs did not increase as quickly. In sum, previous literature suggests that there has been an overall decrease in the costs of health care due to the reform; however, the micro level effects of costs and spending have not been determined.

The third focus of the literature is on access to care post-reform. Research has found that access to care as well as the likelihood of having a usual source of care has increased (Long et al., 2012; Long and Stockley, 2010). Although they also find that there is an increased amount of unmet need in 2010 as compared to 2009, less of it is due to cost barriers. However, Zhu et al. (2010) find no difference in

access to care due to the reform and Maxwell et al. (2011) find that despite a decrease in the disparities in access to care, they are still an issue.

I extend the literature by conducting an empirical analysis with more recent data from the Consumer Expenditure Survey. While previous studies have examined specific effects of the reform on insurance coverage, cost of care, and access to care, I look at the effect of the reform on the ways households allocate their budget towards health care.

IV. Theory

To understand how consumers make decisions about the amount of health care they consume, I use consumer choice theory. The basis of consumer choice theory is the assumption that consumers will behave such that they maximize their utility subject to their budget constraint. This optimization behavior can be determined by deriving the consumer's demand for the specific goods compromising their utility function.

I assume a consumer has two goods, denoted here as X and Y, with prices of P_X and P_Y. The consumer has a utility function taking the form,

$$\boldsymbol{U(X,Y) = f(X,Y)} \tag{4. 1}$$

The consumer's budget constraint is

$$\boldsymbol{I = P_X X + P_Y Y} \tag{4. 2}$$

The Langrangian Multiplier method is used to maximize the consumer's utility subject to their budget constraint:

$$\boldsymbol{max}\, \boldsymbol{U}(\boldsymbol{X},\boldsymbol{Y}) = \boldsymbol{max}\, \boldsymbol{f}(\boldsymbol{X},\boldsymbol{Y}) \qquad (4.3)$$
$$s.t.\;\; P_X X + P_Y Y = I$$

The Langrangian of this problem is therefore

$$\boldsymbol{\theta} = \boldsymbol{f}(\boldsymbol{X},\boldsymbol{Y}) - \boldsymbol{\lambda}(\boldsymbol{P_X X} + \boldsymbol{P_Y Y} - \boldsymbol{I}) \qquad (4.4)$$

The resulting first-order conditions are

$$\frac{\partial \theta}{\partial X} = \frac{\partial f}{\partial X} - \lambda P_X = 0$$
$$\frac{\boldsymbol{\partial \theta}}{\boldsymbol{\partial Y}} = \frac{\boldsymbol{\partial f}}{\boldsymbol{\partial Y}} - \boldsymbol{\lambda P_Y} = \boldsymbol{0} \qquad (4.5)$$
$$\frac{\partial \theta}{\partial \lambda} = P_X X + P_Y Y - I = 0$$

The first-order conditions can be rewritten as

$$\frac{\partial f}{\partial X} = \lambda P_X$$
$$\frac{\boldsymbol{\partial f}}{\boldsymbol{\partial Y}} = \boldsymbol{\lambda P_Y} \qquad (4.6)$$
$$P_X X + P_Y Y = I$$

The first two first-order conditions show that the optimum marginal rate of substitution (MRS) between X and Y is equal to the ratio of the prices:

$$\left.\frac{\boldsymbol{\partial f}}{\boldsymbol{\partial X}}\middle/\frac{\boldsymbol{\partial f}}{\boldsymbol{\partial Y}}\right. = \frac{\boldsymbol{\lambda P_X}}{\boldsymbol{\lambda P_Y}} = \frac{\boldsymbol{P_X}}{\boldsymbol{P_Y}} = \boldsymbol{MRS_{X,Y}} \qquad (4.7)$$

Solving the system of equations of the first-order conditions results in the following functions:

$$\boldsymbol{X} = \boldsymbol{X}^*(\boldsymbol{P_X},\boldsymbol{P_Y},\boldsymbol{I})$$
$$\boldsymbol{Y} = \boldsymbol{Y}^*(\boldsymbol{P_Y},\boldsymbol{P_X},\boldsymbol{I}) \qquad (4.8)$$

$$\boldsymbol{\lambda = \lambda^*(P_X, P_Y, I)}$$

Therefore, the demands for X and Y are functions of the price of X, the price of Y, and income.

Demand functions show how a consumer will change their behavior due to a change in income or the price of the good. However, the consumer's change in behavior is composed of both an income effect and a substitution effect. The income effect describes the change in the quantity demanded with the relative price of the good held constant but the level of utility changing and the substitution effect describes the change in the quantity demanded with the level of utility fixed. The total change in demand for good X, $\frac{dX}{dP_X}$, can be written as

$$\boldsymbol{\frac{dX}{dP_X} = \frac{\partial X}{\partial P_{X|U=U*}} + \left(\frac{\partial X}{\partial I}\right)\left(\frac{\partial I}{\partial P_X}\right)} \quad (4.9)$$

(4.9) shows the total change in X from a one unit change in the price of X. Differentiating the budget constraint (4.2) with respect to the price of X shows that

$$\boldsymbol{\left(\frac{\partial X}{\partial I}\right) = X} \quad (4.10)$$

Plugging (4.10) into (4.9) gives

$$\boldsymbol{\frac{dX}{dP_X} = \frac{\partial X}{\partial P_{X|U=U*}} - X\left(\frac{\partial I}{\partial P_X}\right)} \quad (4.11)$$

(4.11) is the Slutsky equation and shows the change in quantity demanded of X broken down into the substitution effect and the income effect. The first term is the substitution effect, showing the change with the fixed level of utility. The second term is the income effect, showing the change with the relative price of X held constant.

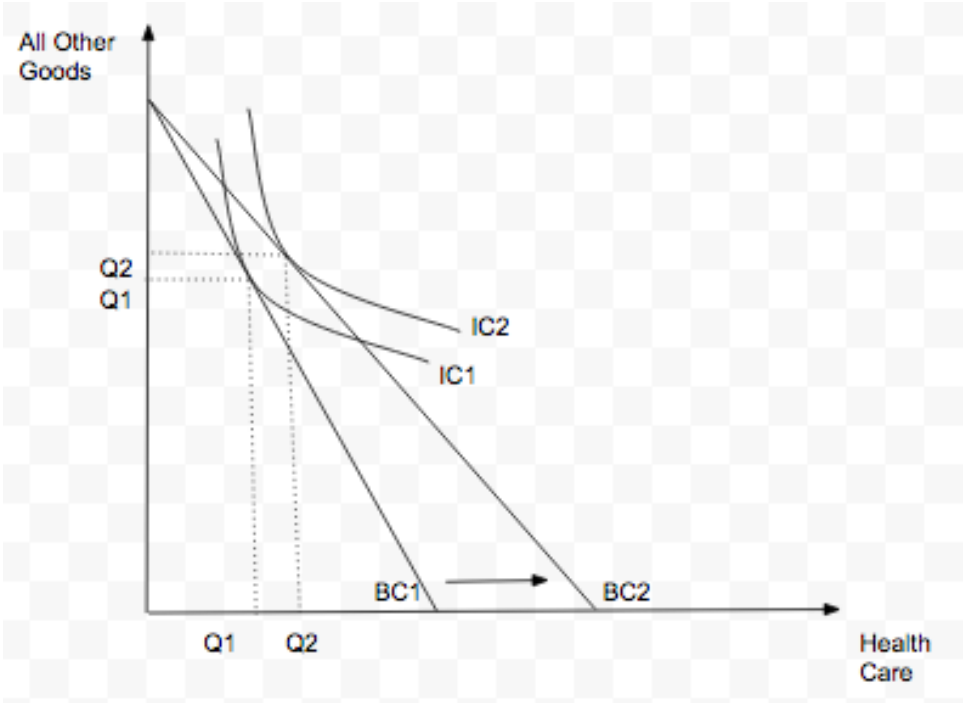
The next step in determining the spending patterns of households is to look at the price change. I assume that there are two goods—health care and all other goods—and that the households experience a change in the price of health care as a result of the reform. I will also assume that the price of health decreases post-reform. I make this assumption for several reasons. First, the literature about the Massachusetts reform has found that insurance premiums, out-of-pocket spending, and health costs in general have decreased (Chandra et al., 2011; Hackmann et al., 2013; Long and Stockley, 2010; and Steinbrook, 2008). Secondly, two main parts of the reform were the expansion of Medicaid benefits and eligibility as well as the introduction of new subsidized insurance programs. Both of these programs aim to decrease the amount that their recipients spend out-of-pocket on health care.

As the Slutsky equation described above shows, changes in demand are composed of both an income effect and a substitution effect. Normal goods, or goods where the quantity demanded increases as income increases, have a negative income effect whereas inferior goods, where the quantity demanded decreases as the income increases, have a positive income effect.

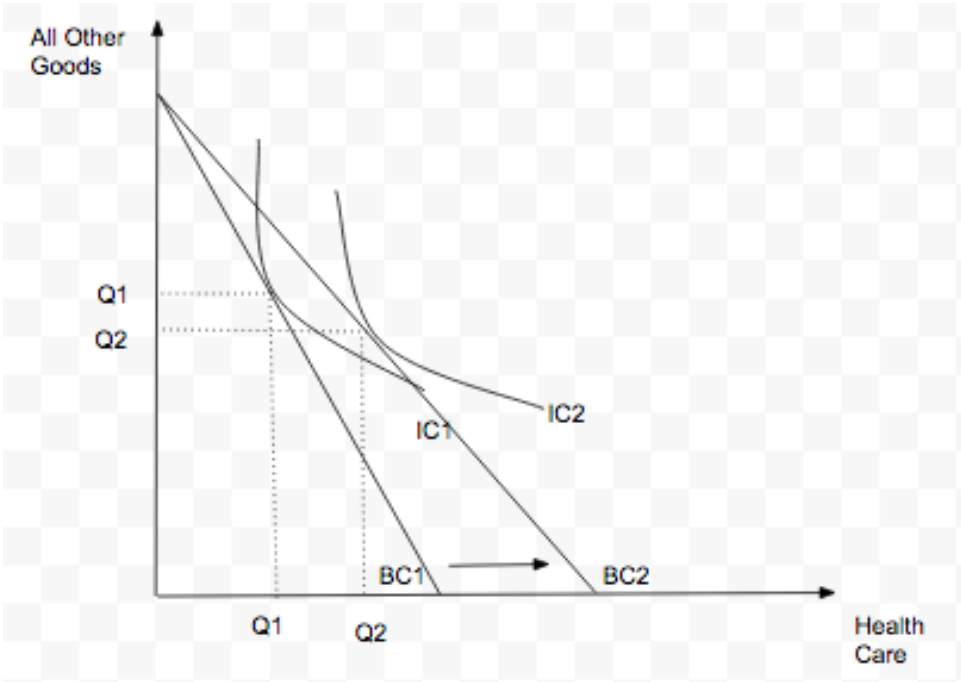
The substitution effect depends on whether the two goods are substitutes or complements. If the goods are substitutes, meaning that as a price of health decreases the quantity demanded of all other goods decreases, the substitution effect will be positive. If the goods are complements, meaning that as the price of health decreases the quantity demanded of all other goods increases, the substitution effect will be negative.

Studies have generally shown that health is a normal good because it is both income and price inelastic, which implies that as the price of health decreases or income increases, quantity demanded of health increases (Ringel, 2002). I therefore assume that health is a normal good and that the income effect is positive.

Below, I show graphically how the quantity demanded of all other goods could change as a result of a decrease in the price of health. The first scenario is if the income effect outweighs the substitution effect. This scenario implies the goods are complements and results in an increase in the quantity of all other goods.



The second scenario is if the substitution effect outweighs the income effect. As seen in the figure below, this results in a decrease in the quantity demanded of all other goods, implying the two goods are substitutes.



While the consumer choice theory described above guides my analysis, price and quantity data are not currently publically available. In the next sections, I further describe the data and empirical model I use in place of calculating demand functions.

V. Data and Summary Statistics

Experimental Design

The gold standard for program evaluation research is the Randomized Controlled Trial (RCT). An RCT involves randomly placing participants into treatment and control groups to minimize any bias and allows for direct observation

of the effect of the treatment. However, RCTs are both expensive and in the case of this research, logistically unfeasible due to the fact that the reform has already been implemented. I must therefore use a quasi-experimental design. The difference between this and the RCT is that participants are not randomly assigned to the treatment or control group. Quasi-experimental methods can take advantage of natural experiments, such as the reform in Massachusetts, that apply a treatment to one group but not another. In a natural experiment, the treatment and control groups are determined by an outside force but can provide observational data that simulates an RCT.

The next best method to determine the affect of the reform on household health spending would be to calculate the demand for health care as seen in the theory detailed in section IV. However, the demand function calculations require data on the prices and quantities of health care that each household faces and these data are not currently publically available.

I therefore use a quasi-experimental difference-in-differences (DD) technique, detailed in section VI, which finds the effect of a treatment by comparing the differences in the treatment group over time with the differences in the control group over time. The DD method calls for an outcome variable as well as explanatory variables, including a treatment designation variable and time variable.

Expenditures and Budget Shares

The main data source used in this paper is the Consumer Expenditure Survey (CEX) from the United States Bureau of Labor Statistics (BLS). The CEX is a two-part

survey of a sample of households across the country that collects information about the expenditures, income, and demographics of households. The CEX has two parts, the quarterly interview and a weekly diary. The data are broken down into Consumer Units (CUs) and the data are collected from a reference person within the household. For the purposes of this paper, I use the quarterly interview data, specifically the data from the Consumer Unit Characteristics and Income files (FMLI), which contains information about CU characteristics, income, and expenditures. The Interview Survey of the CEX is considered to be a rotating panel because CUs provide 4 quarters worth of data but the reference periods and months within each quarter for each CU can be different.

The Consumer Expenditure Survey defines ten main groups of goods: food, alcoholic beverages, housing, apparel and services, transportation, health care, entertainment, personal care, cash contributions, and personal insurance and pensions. Each main group is divided into sub-groups where the summation of the sub-good expenditures is equal to the group expenditures, which in turn sum to the CU's total expenditure.

In this study, I investigate the effects of the healthcare reform on three outcome variables: budget share of total heath expenditures, budget share of health insurance expenditures, and budget share of prescription drugs. I calculate budget shares for each consumer unit by dividing the CU's expenditure on the group by their total expenditure. I calculate the budget shares of the two sub-groups of health, health insurance and prescription drugs, as a share of total expenditures and not just as a share of expenditures on health care.

Treatment and Control Group

The difference-in-differences method requires a treatment group as well as a control group. The treatment group is CUs that reside in Massachusetts and have therefore received the treatment of health care reform. I separate out the CUs located in Massachusetts from the national sample based on the state codes provided.[1] The number of observations in each year (2004-2010) ranges from 424 CUs in 2008 to 524 CUs in 2004 with a total of 3,312 CUs over the entire time period.

The control group represents the counterfactual, or, what would have happened in the treatment group without the treatment. Therefore, the control group should be as similar as possible to the treatment group in the initial time period. Previous studies have used New York as a control group for Massachusetts (Long et al., 2010 and Long and Stockley, 2011). Based off of this, I perform statistical tests to decide if New York is an appropriate control, discussed in more detail below. I also investigate the suitability of Maryland as a potential control state. I determine similarity by looking at total expenditures, expenditures on health, health insurance, and prescription drugs, as well as certain demographic characteristics. I use a t-test to determine whether these variables are statistically significantly different across the control and treatment groups. The null hypothesis of the t-test is that the two groups are not different. Therefore, for the control group to be similar to the treatment group, the t-test should result in t-statistics that are

[1] Massachusetts state codes are not suppressed in any year of the CEX data.

not statistically significant. The results of the t-tests are shown in Table 2. I find that the two groups are not significantly different in terms of total expenditures, health expenditures, prescription drug expenditures, poverty, and homeownership. I therefore use the CUs in New York and Maryland as a control for the CUs in Massachusetts.

I then separate out the CUs in New York and Maryland from the national sample.[2] From 2004-2010, there are 7,571 total CUs sampled in New York with a range of 879 in 2005 to 1,169 in 2004. From 2004-2010, there are 3,065 total CUs sampled in Maryland with a range of 373 in 2008 to 636 in 2004.

I create a binary indicator variable to designate if the CU is in the treatment or control group and also divide the data into two time periods. The pre-reform period is defined as the years 2004 – 2006 and the post-reform period is defined as the years 2007-2010. Even though the law was passed in 2006, I do not begin the post-reform period until 2007 to more accurately reflect the actual implementation.[3]

Table 1 shows summary statistics for expenditures and budget shares of the three outcome variables in the treatment and control groups in both the pre-reform and post-reform time periods.[4] Figures 1 through 3 show the mean expenditures on

[2] New York state codes have been suppressed for some sampled CUs in the state. Maryland state codes may either have some observations that have been re-coded or a least one stratum of observations include re-codes from other states. However, there is no method for determining which CUs may be re-codes from other states.
[3] The actual implementation of the reform did not happen immediately. The reform was rolled out in incremental stages.
[4] I omit CUs with negative values for health expenditures, health insurance expenditures, and prescription drug expenditures from the sample.

health, health insurance, and prescription drugs in the treatment and control groups from 2004 through 2010.

Demographics

In order to control for characteristics other than the reform that might affect a CU's expenditures I include several demographic variables. Demographic data for each CU are collected from the CEX FMLI file. The demographic variables include those that describe the CU as a whole and those that are specific to the reference person. CU demographics of interest include income, race, education, age, family type, and housing type. Controlling for these variables is important because it ensures that any effect they have on health expenditures is not misclassified as a result of the treatment.

Based on the data in the CEX, I create binary variables for the demographic variables of interest. From the income data I create the variable *underFPL* to indicate whether the CU falls below 150% of the federal poverty line (FPL) for their family size in the interview year. Next I create a binary variable to indicate if the CU is a minority or not (*minority*). Minority CUs include those coded as Black, Hispanic, Native American, Asian, Pacific Islander, and Multi-race. Non-minority CUs are those coded as White. Educational attainment is defined by whether the reference person completed college or not (*collegeGrad*). The variable elderly indicates whether the reference person is above 65 years old. I condense the family type variable into a CU with or without children (*children*) and the housing type variable into owns home or not (*ownHome*).

Table 1 shows summary statistics for the demographic variables in the treatment and control groups in both the pre-reform and post-reform time periods.

VI. Empirical Model

The empirical models that I use in this paper are the difference-in-differences as well as the difference-in-difference-in-differences estimation models. I use this quasi-experimental design because it is the next best option given that a Randomized Controlled Trial (RCT) is not possible, as discussed above.

Difference-in-differences (DD)

The difference-in-difference estimation method is based on Ashenfelter and Card (1985). The concept behind the technique is that a treatment effect can be calculated without bias by looking at the difference in the differences in the treatment group before and after the treatment as well the differences between the control group before and after the treatment. This helps to control for consistent and inherent differences between the control group and the treatment group (Imbens and Wooldridge, 2007).

The general model of a difference-in-difference estimation is:

$$\boldsymbol{y = \alpha_0 + \beta_1 T + \beta_2 P + \beta_3 T * P + \varepsilon} \quad (6.1)$$

where

y : outcome variable,

T : treatment dummy,

P : time period dummy.

The coefficients in this estimation are interpreted as:

β_1 : difference between treatment and control groups before treatment,

β_2 : difference between the pre and post treatment periods in treatment group,

β_3 : treatment effect.

The treatment effect, β_3, can also be defined as:

$$\boldsymbol{\beta_3} = \left(\boldsymbol{Y_{T_2}} - \boldsymbol{Y_{T_1}}\right) - \left(\boldsymbol{Y_{C_2}} - \boldsymbol{Y_{C_1}}\right) \quad (6.2)$$

where

Y_{T_2} : outcome of treatment group in period 2,

Y_{T_1} : outcome of treatment group in period 1,

Y_{C_2} : outcome of control group in period 2,

Y_C : outcome of control group in period 1.

Therefore, β_3 measures the difference in difference between the time periods in the treatment group and the difference between the time periods in the control group. β_3 is an unbiased estimate of the treatment effect if:

$$\boldsymbol{E\left(Y_{T_2} - Y_{T_1}\right) - E(Y_2 - Y_1) = \varphi(1 - \rho)} \quad (6.3)$$

where

$E(Y_{T_2} - Y_{T_1})$: expected treatment effect,

$E(Y_2 - Y_1)$: expected overall average effect,

ρ : proportion of total population that is treated.

Difference-in-difference-in-differences (DDD)

The DDD estimation builds off of the DD estimation by adding in a third difference in the treatment and control groups. This means that there is a group A and a group B that represents a more specific population of interest. If the population of interest is A, A becomes a treatment group within the treatment group and B becomes a control group within the control group. I use a DDD estimation to determine if there was any extra affect on two specific groups in Massachusetts: minorities and households under the federal poverty line (*minority* and *underFPL*). Examining the effects on specific populations is important, particularly when the reform was targeted towards certain groups. One goal of the reform was to decrease the disparities in access to care among minorities and low-income households. Finding the extra effect on these two groups can help determine the effectiveness of the reform on two of its targeted populations.

The general model of a difference-in-difference-in-differences estimation is:

$$\boldsymbol{y = \alpha_0 + \beta_1 T + \beta_2 A + \beta_3 T * A + \beta_4 P + \beta_5 P * T + \beta_6 P * A + \beta_7 T * A * P + \varepsilon} \quad (6.4)$$

where

y : outcome variable,

T : treatment dummy,

A : group of interest dummy,

P : time period dummy.

The coefficients in this estimation are interpreted as:

β_1 : difference between treatment and control groups before treatment,

β_2 : difference between the group of interest and control before treatment on average,

β_3 : difference between group of interest and control within treatment group before treatment,

β_4 : difference between pre and post treatment on average,

β_5 : difference between pre and post treatment in treatment group,

β_6 : difference between pre and post treatment in group of interest on average,

β_7 : treatment effect.

The treatment effect, β_7, can also be defined as:

$$\boldsymbol{\beta_7} = \left(\boldsymbol{Y_{T,A,P_2}} - \boldsymbol{Y_{T,A,P_1}}\right) - \left(\boldsymbol{Y_{C,A,P_2}} - \boldsymbol{Y_{C,A,P_1}}\right) - \left(\boldsymbol{Y_{T,B,P_2}} - \boldsymbol{Y_{T,B,P_1}}\right) \quad (6.5)$$

where

Y_{T,A,P_2} : average for group A in treatment group in period 2,

Y_{T,A,P_1} : average for group A in treatment group in period 1,

Y_{C,A,P_2} : average for group A in control group in period 2,

Y_{C,A,P_1} : average for group A in control group in period 2.

Y_{T,B,P_2} : average for group B in treatment group in period 2,

Y_{T,B,P_1} : average for group B in treatment group in period 1.

Therefore, β_7 measures the effect of the policy on group A in the treatment group.

Estimation Equations

The theory and difference-in-differences estimation model suggest that the estimation equations are as follows for each outcome variable:

$$\boldsymbol{y = \alpha_0 + \beta_1 MA + \beta_2 time + \beta_3 MA * time + \varepsilon} \quad (6.\ 6)$$

$$\boldsymbol{y = \alpha_0 + \beta_1 MA + \beta_2 time + \beta_3 MA * time + \beta_4 Demographics + \varepsilon} \quad (6.\ 7)$$

The difference-in-difference-in-differences estimation equations for each outcome variable are:

$$\boldsymbol{y = \alpha_0 + \beta_1 MA + \beta_2 underFPL + \beta_3 MA * underFPL + \beta_4 time + \beta_5 time * MA + \beta_6 time * underFPL + \beta_7 MA * UnderFPL * time + \varepsilon} \quad (6.\ 8)$$

$$\boldsymbol{y = \alpha_0 + \beta_1 MA + \beta_2 underFPL + \beta_3 MA * underFPL + \beta_4 time + \beta_5 time * MA + \beta_6 time * underFPL + \beta_7 MA * UnderFPL * time + \beta_8 Demographics + \varepsilon} \quad (6.\ 9)$$

$$\boldsymbol{y = \alpha_0 + \beta_1 MA + \beta_2 Minority + \beta_3 MA * Minority + \beta_4 time + \beta_5 time * MA + \beta_6 time * Minority + \beta_7 MA * Minority * time + \varepsilon} \quad (6.\ 10)$$

$$\boldsymbol{y = \alpha_0 + \beta_1 MA + \beta_2 Minority + \beta_3 MA * Minority + \beta_4 time + \beta_5 time * MA + \beta_6 time * Minority + \beta_7 MA * Minority * time + \beta_8 Demographics + \varepsilon} \quad (6.\ 11)$$

The Appendix lists all estimation equations.

VII. Analysis

Estimation Issues

I estimate my equations with an Ordinary Least Squares (OLS) estimator. First I test for multicollinearity in my explanatory variables. I use Variation Inflation Factors (VIFS) with a cutoff value of 5 to determine if a given explanatory variable is explained by all of the other explanatory variables. I find that all the tests result in VIFS of less than 5 and can therefore say that extreme multicollinearity is not a problem.

I next test for heteroskedasticity in the error terms. OLS assumes the error terms have a constant variance and are homoscedastic. First I run a Breusch-Pagan test to describe the extent to which the explanatory variables explain the error term. The null hypothesis is that the residuals are homoscedastic. All of the Breusch-Pagan tests result in p-values less than 0.05, which means that we can reject the null hypothesis and assume the residuals are heterskedastic. I also run a White test for heteroskedasticity. Again the null hypothesis is that the residuals are homoscedastic. The results from the White tests were mixed. To correct for the heteroskedasticity in the data, I use robust standard errors. Even though the White

test is unclear as to the presence of heteroskedasticity, the data are large so hypothesis testing will still be accurate with robust standard errors.

Main Results

I run six different specifications for each of the outcome variables, health expenditures as a share of total expenditures, prescription drug expenditures as a share of total expenditures, and health insurance expenditures as a share of total expenditures.

Health Shares:

The regression results for the health share specifications are shown in Table 3. Equations (1) and (2) show the difference-in-differences without and with demographics, respectively. The interaction between Massachusetts (MA) and time shows the effect of the law is positive, very small in magnitude, and not statistically significant in both (1) and (2).

Equations (3) and (4) show the difference-in-difference-in-differences estimation with the sub group of CUs under the federal poverty line (FPL) without and with demographics, respectively. The interaction term that shows the effect of the law on CUs below the FPL is negative and statistically insignificant in both equations.

Equations (5) and (6) show the difference-in-difference-in-differences estimation with the sub group of minority CUs without and with demographics, respectively. The interaction term that shows the effect of the law on minorities is positive and statistically significant. The coefficient in (5) says that as a result of the law, minorities spent 0.0187 percentage points more on their health share as compared to everyone else. The coefficient in (6) says that the law resulted in minorities spending 0.0133 percentage points more on their health share.

The demographic variables in equations (2), (3), (4), (5), and (6) are all statistically significant. The coefficients for CUs who are under the FPL, elderly CUs, and CUs who own a home are positive. The values show that CUs below the FPL spend a higher percentage of their total budget on health than those above the FPL, elderly CUs spend more of their budget on health than non-elderly, and homeowners spend a higher percentage of their budget on health.

The coefficients for CUs who are minorities, have children, and are college graduates are all negative. This means that minorities spend a lower share of their budget on health than white CUs, CUs with children spend a lower share on health than CUs with children, and college graduates spend a lower share than non-college graduates.

Health Insurance Shares:

The regression results for the health insurance as a share of total expenditure specifications are shown in Table 4. Equations (1) and (2) show the difference-in-differences without and with demographics, respectively. The

interaction between MA and time that shows the effect of the law is positive in (1) but negative in (2), very small in magnitude, and not statistically significant in both (1) and (2).

Equations (3) and (4) show the difference-in-difference-in-differences estimation with the sub group of CUs under the FPL without and with demographics, respectively. The interaction term that shows the effect of the law on CUs below the FPL is negative and statistically insignificant in both equations.

Equations (5) and (6) show the difference-in-difference-in-differences estimation with the sub group of minority CUs without and with demographics, respectively. The interaction term that shows the effect of the law on minorities is positive and statistically significant in (5) but not (6). The coefficient in (5) says that as a result of the law, minorities spent 0.0116 percentage points more on their health insurance as a share compared to everyone else. However, because the treatment effect was not statistically significant when demographics were added (6), this suggests that the statistical significance in (5) may not be the true effect of the law.

The demographic variables in (2), (3), (4), (5), and (6) are statistically significant, except for minority in (6). The coefficients for CUs who are under the FPL, college graduates, and CUs who own a home are positive. The values show that CUs below the FPL spend a higher percentage of their total budget on health than those above the FPL, college graduates spend more of their budget on health than non-college graduates, and homeowners spend a higher percentage of their budget on health. The coefficients for CUs who are minorities, have children, and are elderly

are all negative. This means that minorities spend a lower share of their budget on health than white CUs, CUs with children spend a lower share on health than CUs with children, and the elderly spend a lower share of their budget on health than non-elderly.

Prescription Drug Shares:

The results for the prescription drug regressions are shown in Table 5. Equations (1) and (2) show the difference-in-differences without and with demographics, respectively. The interaction between MA and time that shows that the effect of the law in both (1) and (2) is negative, very small in magnitude, and not statistically significant.

Equations (3) and (4) show the difference-in-difference-in-differences estimation with the sub group of CUs under the FPL without and with demographics, respectively. The interaction term that shows the effect of the law on CUs below the FPL is positive and statistically insignificant in both equations.

Equations (5) and (6) show the difference-in-difference-in-differences estimation with the sub group of minority CUs without and with demographics, respectively. The interaction term that shows the effect of the law on minorities is positive and statistically significant in (5) and (6). The coefficient say that as a result of the law, minorities spent 0.00914 (Equation (1)) and 0.00825 (Equation (2)) percentage points more on their health insurance as a share compared to everyone else.

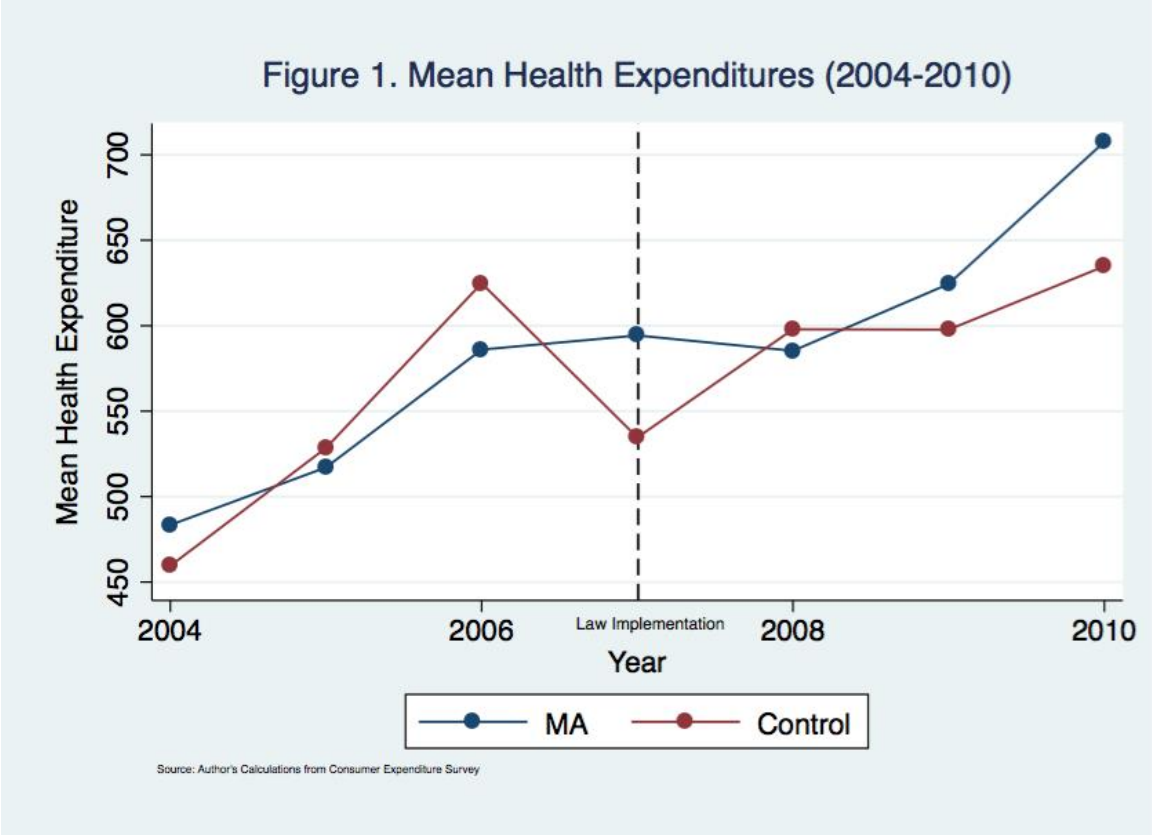
The demographic variables other the owning a home are statistically significant in (2), (3), (4), (5), and (6). The coefficients for CUs who are under the FPL or elderly are positive. The values show that CUs below the FPL spend a higher percentage of their total budget on health than those above the FPL and the elderly spend a higher percentage of their budget on health than the non-elderly. The coefficients for CUs who are minorities, have children, and are college graduates are all negative. This means that minorities spend a lower share of their budget on health than white CUs, CUs with children spend a lower share on health than CUs with children, and college graduates spend a lower share of their budget on health than non-college graduates.

VIII. Conclusions

The regression results do not provide enough evidence that the Massachusetts health care reform had a significant effect on the ways households allocate their spending on health. The difference-in-difference-in-differences focused on minorities did show some significance in total health shares and prescription drug shares. The coefficient for the effect of the law was positive in both cases, which means that the law caused these CUs to spend a higher percentage of their total budget on health expenses. This could possibly be due to minorities becoming insured under the new mandate and expansion of coverage eligibility, therefore bringing their health spending from a negligible amount to a higher amount. This could be reflected in a higher budget share.

One limitation of this analysis is that it can be difficult to interpret budget shares. Calculating budget shares is not the same thing as calculating the quantity demanded so I cannot say with certainty that the quantities of health, health insurance, and prescription drugs changed. If the budget share changes, it could be due to a change in price, quantity, or total expenditures. However, estimating budget shares can offer some insight into the ways that households change their spending behavior.

These results raise questions that require future research. The first question is why did minorities experience a statistically significant treatment effect but households under the federal poverty line did not? Answering this question would require a closer look at the differences between the makeup of the minority group and the low-income group. Another topic that needs to be investigated further is the actual health outcomes of the CUs. It may be possible that the expenditures on health for minorities were below the optimal level before the law and the law increased their expenditures up to a level that is consistent with good health outcomes. If so, it could be argued that the law had beneficial impacts on minorities. Overall, future research is needed to fully understand the impacts of health care reform.



IX. Tables and Figures

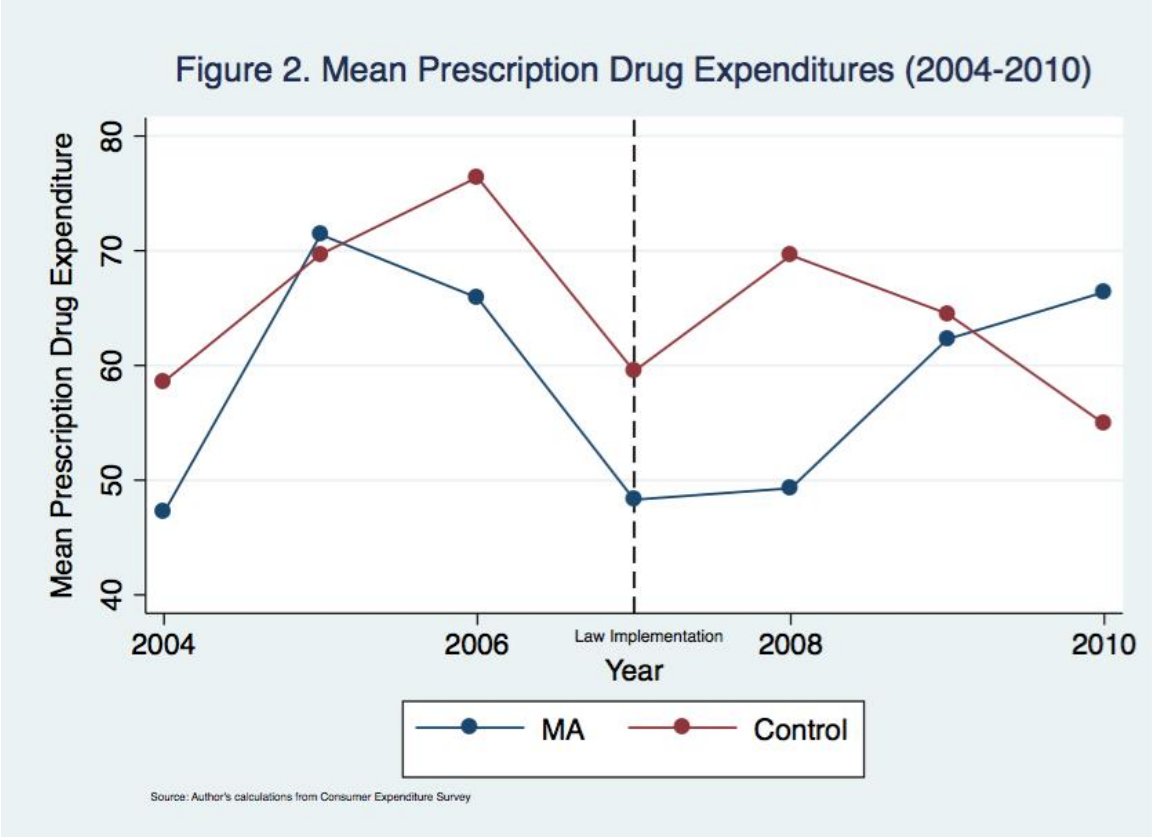


Figure 2. Mean Prescription Drug Expenditures (2004-2010)
Mean Prescription Drug Expenditure
40
50
60
70
80
2004
2006
Law Implementation
2008
2010
Year
MA
Control
Source: Author's calculations from Consumer Expenditure Survey

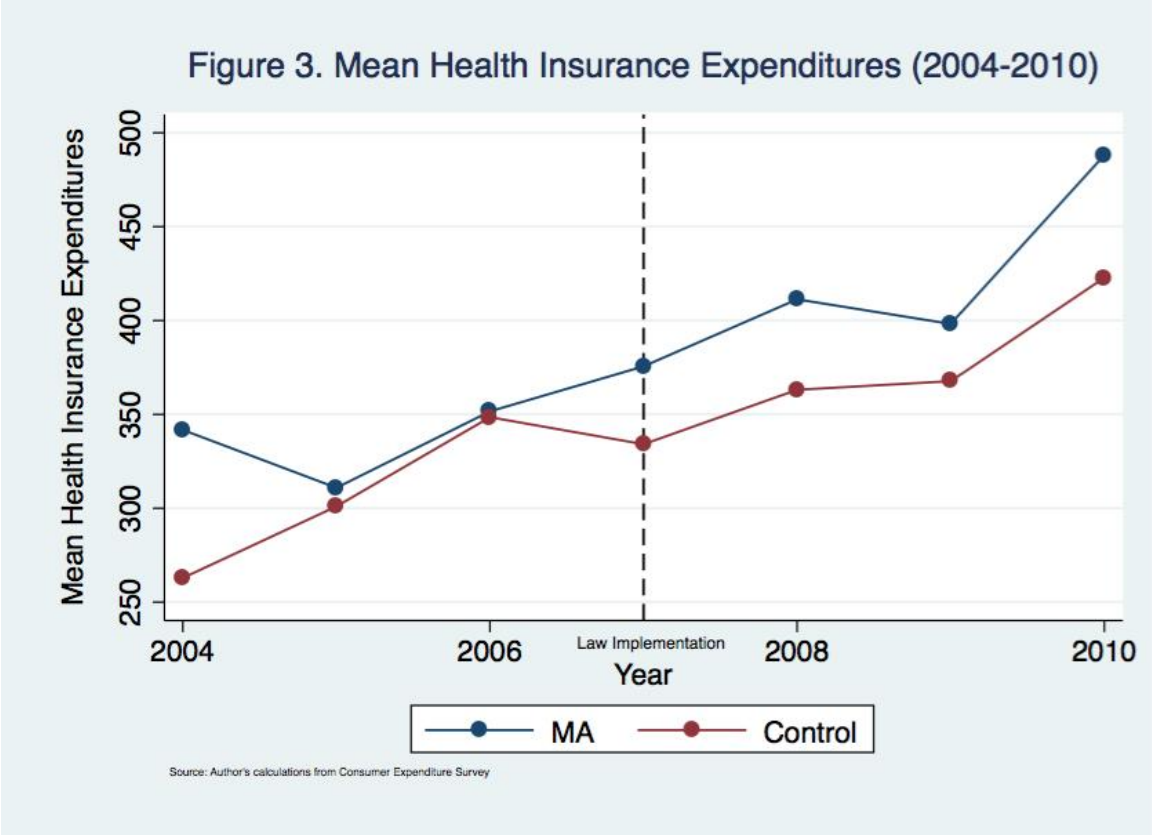


Figure 3. Mean Health Insurance Expenditures (2004-2010)
Mean Health Insurance Expenditures
250
300
350
400
450
500
2004
2006
Law Implementation
2008
2010
Year
MA
Control
Source: Author's calculations from Consumer Expenditure Survey

Table 1. Summary Statistics

	Massachusetts				Control Group (New York and Maryland)			
	Pre (N=1477)		Post (N=1835)		Pre (N=4581)		Post (N=6055)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Health Expenditures	527.82	810.62	629.88	814.18	531.30	847.87	591.21	810.25
Health Insurance Expenditures	335.22	419.26	419.30	461.10	300.80	435.10	372.00	506.60
Prescription Drug Expenditures	61.02	147.10	57.10	155.70	67.40	203.30	62.10	167.40
share Health	8.1%	8.7%	8.1%	8.2%	8.1%	8.7%	7.7%	79.8%
share Health Insurance	5.6%	6.7%	5.8%	6.2%	5.2%	6.1%	5.3%	6.1%
share Prescription Drugs	1.2%	2.9%	0.8%	1.8%	1.2%	3.2%	0.9%	2.2%
underFPL	15.4%	36.1%	13.6%	34.3%	16.6%	37.2%	14.4%	35.1%
Minority	12.6%	33.2%	14.1%	34.8%	30.7%	46.1%	32.2%	46.7%
Children	34.6%	47.6%	31.0%	46.3%	28.8%	45.3%	28.5%	45.1%
CollegeGrad	45.8%	49.8%	47.7%	49.9%	40.1%	49.0%	44.9%	49.7%
Elderly	21.5%	41.1%	22.7%	41.9%	28.8%	45.3%	27.9%	44.8%
OwnHome	68.9%	46.3%	69.8%	45.9%	69.5%	46.0%	66.1%	47.3%

Source: Author's calculations from Consumer Expenditure Survey, Bureau of Labor Statistics

Table 2. T-test Results

Variable	t-test
Total Expenditures	0.137
Health Expenditures	0.890
Health Insurance Expenditures	0.008
Prescription Drug Expenditures	0.263
Minority	0.000
underFPL	0.306
Children	0.000
CollegeGrad	0.000
Elderly	0.000
OwnHome	0.651

Source: Author's calculations from Consumer Expenditure Survey, Bureau of Labor Statistics

Table 3. Regressions Results for Health Shares

VARIABLES	Difference-in-differences		Difference-in-difference-in-differences			
	(1)	(2)	(3)	(4)	(5)	(6)
MA	0.000721	0.00424*	0.0012	0.00479*	-0.000365	0.00474*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time	-0.00334*	-0.00182	0.00064	0.000385	-0.000635	-0.000251
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time * MA	0.00267	0.000429	0.00373	0.0014	-0.00121	-0.00232
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
UnderFPL		0.0117***	0.0447***	0.0210***		0.0117***
		(0.00)	(0.00)	(0.00)		(0.00)
Minority		-0.0135***		-0.0136***	-0.0145***	-0.0116***
		(0.00)		(0.00)	(0.00)	(0.00)
Children		-0.00747***		-0.00731***		-0.00752***
		(0.00)		(0.00)		(0.00)
CollegeGrad		-0.00686***		-0.00697***		-0.00692***
		(0.00)		(0.00)		(0.00)
Elderly		0.0673***		0.0671***		0.0673***
		(0.00)		(0.00)		(0.00)
OwnHome		0.00469*		0.00468*		0.00464*
		(0.00)		(0.00)		(0.00)
UnderFPL * MA			0.000375	-0.00315		
			(0.01)	(0.01)		
UnderFPL * Time			-0.0208***	-0.0139***		
			(0.01)	(0.01)		
UnderFPL * MA * Time			-0.0103	-0.00853		
			(0.01)	(0.01)		

VARIABLES	Difference-in-differences		Difference-in-difference-in-differences			
	(1)	(2)	(3)	(4)	(5)	(6)
Minority * MA					-0.0121**	-0.00118
					(0.01)	(0.01)
Minority * Time					-0.00776**	-0.00497
					(0.00)	(0.00)
Minority * MA *Time					0.0187**	0.0133*
					(0.01)	(0.01)
Constant	0.0809***	0.0654***	0.0735***	0.0640***	0.0854***	0.0649***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Observations	13,993	13,993	13,993	13,993	13,993	13,993
R-squared	0	0.117	0.015	0.118	0.008	0.118

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Consumer Expenditure Survey, Bureau of Labor Statistics

Table 4. Regressions Results for Health Insurance Shares

VARIABLES	Difference-in-differences		Difference-in-difference-in-differences			
	(1)	(2)	(3)	(4)	(5)	(6)
MA	0.00372*	0.00741***	0.00417**	0.00782***	0.00433*	0.00833***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time	0.000653	0.00192*	0.00264**	0.00260**	0.00336**	0.00392***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time * MA	0.00154	-0.000289	0.00308	0.00117	-0.00145	-0.00245
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
UnderFPL		0.00840***	0.0314***	0.0126***		0.00841***
		(0.00)	(0.00)	(0.00)		(0.00)
Minority		-0.00511***		-0.00526***	-0.00409**	-0.00172
		(0.00)		(0.00)	(0.00)	(0.00)
Children		-0.00535***		-0.00530***		-0.00538***
		(0.00)		(0.00)		(0.00)
CollegeGrad		0.0501***		0.0499***		0.0500***
		(0.00)		(0.00)		(0.00)
Elderly		-0.00842***		-0.00847***		-0.00851***
		(0.00)		(0.00)		(0.00)
OwnHome		0.00515***		0.00513***		0.00513***
		(0.00)		(0.00)		(0.00)
UnderFPL * MA			-0.000541	-0.00259		
			(0.01)	(0.01)		
UnderFPL * Time			-0.00901**	-0.00411		
			(0.00)	(0.00)		
UnderFPL * MA * Time			-0.0129	-0.0114		
			(0.01)	(0.01)		

VARIABLES	Difference-in-differences		Difference-in-difference-in-differences			
	(1)	(2)	(3)	(4)	(5)	(6)
Minority * MA					-0.0106***	-0.0024
					(0.00)	(0.00)
Minority * Time					-0.00824***	-0.00639***
					(0.00)	(0.00)
Minority * MA *Time					0.0116**	0.0074
					(0.01)	(0.01)
Constant	0.0523***	0.0394***	0.0471***	0.0388***	0.0536***	0.0384***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	13,993	13,993	13,993	13,993	13,993	13,993
R-squared	0.001	0.171	0.023	0.172	0.006	0.171

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Consumer Expenditure Survey, Bureau of Labor Statistics

Table 5. Regressions Results for Prescription Shares

VARIABLES	Difference-in-differences		Difference-in-difference-in-differences			
	(1)	(2)	(3)	(4)	(5)	(6)
MA	-0.000257	0.0004	-6.85E-06	0.000652	0.000104	0.000886
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time	-0.00363***	-0.00329***	-0.00256***	-0.00256***	-0.00369***	-0.00348***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time * MA	-0.00051	-0.000912	-0.000678	-0.00111	-0.00165	-0.00190*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
UnderFPL		0.00445***	0.0115***	0.00720***		0.00444***
		(0.00)	(0.00)	(0.00)		(0.00)
Minority		-0.00222***		-0.00223***	-0.00255***	-0.00262***
		(0.00)		(0.00)	(0.00)	(0.00)
Children		-0.00206***		-0.00201***		-0.00204***
		(0.00)		(0.00)		(0.00)
CollegeGrad		-0.00262***		-0.00265***		-0.00259***
		(0.00)		(0.00)		(0.00)
Elderly		0.00995***		0.00988***		0.00997***
		(0.00)		(0.00)		(0.00)
OwnHome		0.000228		0.000221		0.000202
		(0.00)		(0.00)		(0.00)
UnderFPL * MA			-0.000733	-0.00147		
			(0.00)	(0.00)		
UnderFPL * Time			-0.00568***	-0.00466**		
			(0.00)	(0.00)		
UnderFPL * MA * Time			0.000458	0.00092		
			(0.00)	(0.00)		

VARIABLES	Difference-in-differences		Difference-in-difference-in-differences			
	(1)	(2)	(3)	(4)	(5)	(6)
Minority * MA					-0.00646***	-0.00441***
					(0.00)	(0.00)
Minority * Time					0.000308	0.000605
					(0.00)	(0.00)
Minority * MA *Time					0.00914***	0.00825***
					(0.00)	(0.00)
Constant	0.0120***	0.0106***	0.0101***	0.0102***	0.0128***	0.0107***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	13,993	13,993	13,993	13,993	13,993	13,993
R-squared	0.005	0.057	0.02	0.058	0.008	0.058

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Source: Consumer Expenditure Survey, Bureau of Labor Statistics

X. Appendix

Difference-in-differences:

$$healthShare = \alpha_0 + \beta_1 MA + \beta_2 time + \beta_3 MA * time + \varepsilon \quad (10.1)$$

$$healthShare = \alpha_0 + \beta_1 MA + \beta_2 time + \beta_3 MA * time + \beta_4 underFPL + \beta_5 Minority + \beta_6 Children + \beta_7 collegeGrad + \beta_8 Elderly + \beta_9 ownHome + \varepsilon \quad (10.2)$$

$$healthInsShare = \alpha_0 + \beta_1 MA + \beta_2 time + \beta_3 MA * time + \varepsilon \quad (10.3)$$

$$healthInsShare = \alpha_0 + \beta_1 MA + \beta_2 time + \beta_3 MA * time + \beta_4 underFPL + \beta_5 Minority + \beta_6 Children + \beta_7 collegeGrad + \beta_8 Elderly + \beta_9 ownHome + \varepsilon \quad (10.4)$$

$$presShare = \alpha_0 + \beta_1 MA + \beta_2 time + \beta_3 MA * time + \varepsilon \quad (10.5)$$

$$presShare = \alpha_0 + \beta_1 MA + \beta_2 time + \beta_3 MA * time + \beta_4 underFPL + \beta_5 Minority + \beta_6 Children + \beta_7 collegeGrad + \beta_8 Elderly + \beta_9 ownHome + \varepsilon \quad (10.6)$$

Difference-in-difference-in-differences:

$$healthShare = \alpha_0 + \beta_1 MA + \beta_2 underFPL + \beta_3 MA * underFPL + \beta_4 time + \beta_5 time * MA + \beta_6 time * underFPL + \beta_7 MA * UnderFPL * time + \varepsilon \quad (10.7)$$

$$healthShare = \alpha_0 + \beta_1 MA + \beta_2 underFPL + \beta_3 MA * underFPL + \beta_4 time + \beta_5 time * MA + \beta_6 time * underFPL + \beta_7 MA * UnderFPL * time + \beta_8 Minority + \beta_9 Children + \beta_{10} collegeGrad + \beta_{11} Elderly + \beta_{12} ownHome + \varepsilon \quad (10.8)$$

$$healthShare = \alpha_0 + \beta_1 MA + \beta_2 Minority + \beta_3 MA * Minority + \beta_4 time + \beta_5 time * MA + \beta_6 time * Minority + \beta_7 MA * Minority * time + \varepsilon \quad (10.9)$$

$$healthShare = \alpha_0 + \beta_1 MA + \beta_2 Minority + \beta_3 MA * Minority + \beta_4 time + \beta_5 time * MA + \beta_6 time * Minority + \beta_7 MA * Minority * time + \beta_8 underFPL + \beta_9 Children + \beta_{10} collegeGrad + \beta_{11} Elderly + \beta_{12} ownHome + \varepsilon \quad (10.10)$$

$$healthInsShare = \alpha_0 + \beta_1 MA + \beta_2 underFPL + \beta_3 MA * underFPL + \beta_4 time + \beta_5 time * MA + \beta_6 time * underFPL + \beta_7 MA * UnderFPL * time + \varepsilon \quad (10.11)$$

$$healthInsShare = \alpha_0 + \beta_1 MA + \beta_2 underFPL + \beta_3 MA * underFPL + \beta_4 time + \beta_5 time * MA + \beta_6 time * underFPL + \beta_7 MA * UnderFPL * time + \beta_8 Minority + \beta_9 Children + \beta_{10} collegeGrad + \beta_{11} Elderly + \beta_{12} ownHome + \varepsilon \quad (10.12)$$

$$healthInsShare = \alpha_0 + \beta_1 MA + \beta_2 Minority + \beta_3 MA * Minority + \beta_4 time + \beta_5 time * MA + \beta_6 time * Minority + \beta_7 MA * Minority * time + \varepsilon \quad (10.13)$$

$$healthInsShare = \alpha_0 + \beta_1 MA + \beta_2 Minority + \beta_3 MA * Minority + \beta_4 time + \beta_5 time * MA + \beta_6 time * Minority + \beta_7 MA * Minority * time + \beta_8 underFPL + \beta_9 Children + \beta_{10} collegeGrad + \beta_{11} Elderly + \beta_{12} ownHome + \varepsilon \quad (10.14)$$

$$presShare = \alpha_0 + \beta_1 MA + \beta_2 underFPL + \beta_3 MA * underFPL + \beta_4 time + \beta_5 time * MA + \beta_6 time * underFPL + \beta_7 MA * UnderFPL * time + \varepsilon \quad (10.15)$$

$$presShare = \alpha_0 + \beta_1 MA + \beta_2 underFPL + \beta_3 MA * underFPL + \beta_4 time + \beta_5 time * MA + \beta_6 time * underFPL + \beta_7 MA * UnderFPL * time + \beta_8 Minority + \beta_9 Children + \beta_{10} collegeGrad + \beta_{11} Elderly + \beta_{12} ownHome + \varepsilon \quad (10.16)$$

$$presShare = \alpha_0 + \beta_1 MA + \beta_2 Minority + \beta_3 MA * Minority + \beta_4 time + \beta_5 time * MA + \beta_6 time * Minority + \beta_7 MA * Minority * time + \varepsilon \quad (10.17)$$

$$presShare = \alpha_0 + \beta_1 MA + \beta_2 Minority + \beta_3 MA * Minority + \beta_4 time + \beta_5 time * MA + \beta_6 time * Minority + \beta_7 MA * Minority * time + \beta_8 underFPL + \beta_9 Children + \beta_{10} collegeGrad + \beta_{11} Elderly + \beta_{12} ownHome + \varepsilon \quad (10.18)$$

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