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Do premium tax credits increase private health insurance coverage? Evidence from the 2006 Massachusetts health care reform

Jesse M. Hinde *

Department of Public Policy, University of North Carolina at Chapel Hill, Abernethy Hall, CB #3435, Chapel Hill, NC 27599-3435, United States

HIGHLIGHTS

- First study to examine effects of premium tax credits in Massachusetts.
- Premium tax credits appear increase private health insurance.
- Regression discontinuity could be useful to similar tax credits in the ACA.

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ABSTRACT

I use the Current Population Survey March Supplement and a regression discontinuity design to demonstrate a positive impact of premium tax credits, implemented as a part of the 2006 health reform in Massachusetts, on non-group private health insurance coverage.

1. Introduction

The costs of health care and health insurance (HI) have increased dramatically over the past several decades in the United States. Many individuals and families have relied on employer-sponsored insurance (ESI) for affordable HI, but ESI has eroded recently as costs climb. To attempt to address this, many states have expanded public health insurance (PHI) to cover low-income families. In 2006, Massachusetts implemented a novel health reform that provided a marketplace for individuals to purchase HI directly. The marketplace was coupled with an individual mandate that ensured a large enough risk pool to contain premiums. To further incentivize participation, Massachusetts subsidized premiums for individuals below 300% of the federal poverty level (FPL).

Extensive literature has examined the broad impact of the Massachusetts reforms on the insured rate (e.g., Pande et al., 2011) and a variety of health and health care utilization outcomes (e.g., Kolstad and Kowalski, 2012). A methodological difficulty with such an extensive set of policies is to isolate the effects of different policy components. No study to date has looked directly at the tax credits. This study uses regression discontinuity (RD) to compare non-group private insurance coverage of individuals just below 300% FPL who were eligible for a tax credit to individuals just above who were not eligible.

The tax credits reduce the up-front cost of obtaining HI, but they still require the individual to contribute some of the cost. Tax credits represent a new form of income transfer, and their effect has little empirical evidence. Evidence to date has focused on individuals who are laid off or are self-employed, and associated subsidies have produced modest, positive impacts. Given static premium costs, some consumers may not want HI regardless of the subsidy, and some may want it without a subsidy. From a policy maker's perspective, the population of interest is those on the margin of purchasing insurance. The tax credit must be large enough

Abbreviations: CPS, Current Population Survey; ESI, Employer-sponsored insurance; FPL, Federal poverty level; HI, Health insurance; IPI, Individually purchased insurance; PHI, Public health insurance; RD, Regression discontinuity.

* Tel.: +1 919 475 4928.
E-mail address: hinde@live.unc.edu.

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Table 1
Weighted summary statistics, 230%–370% FPL.

Characteristic	1999–2006		2007–2009	
	$N = 2578$		$N = 804$	
	Mean	SE	Mean	SE
Any HI	0.82	(0.01)	0.93	(0.010)
ESI	0.74	(0.01)	0.74	(0.017)
IPI	0.04	(0.00)	0.06	(0.009)
PHI	0.04	(0.00)	0.13	(0.013)
Age	38.53	(0.26)	39.45	(0.498)
Female	0.53	(0.01)	0.52	(0.019)
Race				
White	0.86	(0.01)	0.83	(0.014)
Black	0.08	(0.01)	0.09	(0.011)
Other/multiple	0.06	(0.01)	0.08	(0.009)
Hispanic	0.10	(0.01)	0.08	(0.009)
Marital status				
Married	0.49	(0.01)	0.49	(0.019)
Previously married	0.14	(0.01)	0.14	(0.013)
Never married	0.37	(0.01)	0.37	(0.019)
Household size	3.07	(0.04)	3.06	(0.071)

Note: Summary statistics before and after health reform.

to encourage participation for consumers who want insurance but not at pre-reform prices. I test whether the tax credits were large enough to increase participation.

2. Materials and methods

The Current Population Survey (CPS) was chosen because it captures income, HI, and demographics before and after the 2006 Massachusetts health reform (Flood et al., 2015). The pre-reform period comprises calendar years 1999 through 2006, and the post-reform period comprises calendar years 2007 through 2009. The sample includes adults aged 18–64 and excludes veterans and individuals with imputed HI responses.

Although individuals can report multiple types of HI in a year, I used three exclusive categories for HI based on guidance from the literature: the primary outcome, individually purchased insurance (IPI); ESI; and PHI. If an individual reports ESI, they are excluded from being in the IPI or PHI. Individuals who report any ESI or IPI are not included in the PHI.

Using a RD design, the forcing variable is the respondent's income relative to the FPL. FPL is the ratio of total family income to the federally determined poverty threshold. The threshold is based on the size of the family. I focus on 300% FPL, which is the upper limit for tax credit eligibility. The tax credit had an average value of approximately $1500 just below 300% FPL. A series of individual variables is also used to control for potential confounding factors: age, gender, race, ethnicity, marital status, family size, urbanicity, education, and self-reported health status.

I estimated the RD model at 300% FPL using both parametric and nonparametric models. The base parametric specification is:

$$HI_i = \alpha + \beta_1 SUB(\text{FPL} < 300)_i + \beta_2 \text{FPL}(x - 300)_i + \beta_3 SUB(\text{FPL} < 300)_i * \text{FPL}\,(x - 300)_i + \delta \boldsymbol{X}_i + \tau_i + \varepsilon_i$$

where HI is a binary HI indicator, SUB is a binary indicator for below 300% FPL. FPL is centered at 300%, $\boldsymbol{X}$ is a vector of individual demographics described above, and τ_i are year fixed effects. ε_i is assumed to be an independently and identically distributed error term. β_1 is the treatment effect at the discontinuity. All models use the HI-specific probability weight. I estimate the above equation with and without $\boldsymbol{X}$ and τ_i and with higher-order FPL terms. Standard errors are clustered on the FPL for the parametric models (Lee and Card, 2008). I also pooled each model and computed a difference-in-differences effect at the cutoff. Lastly, a non-parametric RD was estimated using local linear regression with a triangle kernel density estimator.

Following Imbens and Lemieux (2008), four sensitivity and falsification tests were used to test the robustness of the results: checking for false cutoffs, changing the bandwidth around the cutoff, McCrary's (2008) test for manipulation of the forcing variable, and discontinuities in demographic characteristics. An additional test examined nonrandom heaping (Barecca et al., 2011). The sensitivity tests do not meaningfully alter the results of this study.

One particular concern suggested by Shu (2016) was manipulation in the FPL in Massachusetts around 300% FPL using American Community Survey data. I did not find visual or statistical evidence of manipulation in the CPS using more years than Shu (2016). With self-reported income, families tend to report incomes rounded to the nearest $1000 or $5000 increment. Since the FPL variable is created by dividing income by the poverty cutoff, and the poverty cutoff is determined by family size, this creates lumpiness in the histogram (see Online Appendix Figures 1 and 2).

3. Results

Table 1 presents weighted summary statistics for the 1999–2006 and 2007–2009 samples between 230% and 370% FPL. The summary statistics demonstrated a slight increase in IPI and PHI across time. There was little change in demographic characteristics of the sample across time, including education and self-reported health (not presented).

Fig. 1 presents the main RD results graphically for the post-reform periods for all outcomes, and Table 2 presents statistical estimates for the effect shown in Fig. 1. The bottom left panel of Fig. 1 shows an increase in IPI just below 300% FPL in the post-reform period and no detectable effect in the pre-reform period. The nonparametric estimates for IPI are a statistically significant increase of 8.4% points, and the cubic model estimates a 19.4% point effect. The linear and difference-in-differences models are similar in magnitude to the non-parametric model, but they are not statistically significant.

Although IPI is the primary outcome, the remainder of Fig. 1 and Table 2 present the broader effects on other HI outcomes. The upper left panel of Fig. 1 shows that any HI coverage decreased slightly in the post-reform period just below 300% FPL. The estimate for that effect was 4%–5% points, and it was not statistically significant. Although imprecise, this result suggests that the increase in coverage in IPI due to the subsidies was offset by a general decrease in coverage.

The right two panels of Fig. 1 explain the decrease in any HI coverage. There was a small decrease in the post-reform period for ESI just below 300% FPL, but it was not statistically significant. There was a much larger decrease in PHI, but the visual evidence in the PHI panel was not as convincing as the IPI panel: there was not a clear break in the PHI trend and much more noise. Still, Table 2 suggests that the reduction in PHI was statistically significant in the post-reform period, ranging in effect size from 12% to 18% points.

One potential explanation for the overall decrease in HI and large decrease in PHI is crowd-out. However, there were not concurrent Medicaid policy changes at 300% FPL. These effects could instead be explained by volatility between ESI and PHI due to the Great Recession. For the bin proportions of ESI and PHI in Fig. 1, spikes in ESI coverage line up with decreases in PHI and vice versa. There were not enough observations to test this hypothesis by looking at years separately.

The permutation testing also provided a meaningful check for interpreting the ESI/PHI effect. The effect for IPI was largest in magnitude and the test statistic relative to all surrounding points in the FPL distribution (see Online Appendix Figure 3), suggesting a valid treatment effect. The permutation tests were much less clear for ESI and PHI where there were large effects in both directions at multiple false cutoffs between 220% and 300% FPL, suggesting