

NBER WORKING PAPER SERIES

THE IMPACT OF HEALTH INSURANCE ON PREVENTIVE CARE AND HEALTH BEHAVIORS:
EVIDENCE FROM THE 2014 ACA MEDICAID EXPANSIONS

Kosali Simon
Aparna Soni
John Cawley

Working Paper 22265
<http://www.nber.org/papers/w22265>

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2016

For helpful comments, we thank Robert Kaestner, Christopher Robertson, Christopher Carpenter, Thomas DeLeire, Haizhen Lin, Daniel Sacks, and seminar participants at Northwestern University and Indiana University. Cawley thanks the Robert Wood Johnson Foundation for financial support through an Investigator Award in Health Policy Research. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

At least one co-author has disclosed a financial relationship of potential relevance for this research. Further information is available online at <http://www.nber.org/papers/w22265.ack>

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2016 by Kosali Simon, Aparna Soni, and John Cawley. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

The Impact of Health Insurance on Preventive Care and Health Behaviors: Evidence from the 2014 ACA Medicaid Expansions

Kosali Simon, Aparna Soni, and John Cawley

NBER Working Paper No. 22265

May 2016

JEL No. I12,I13,I28

ABSTRACT

The U.S. population receives suboptimal levels of preventive care and has a high prevalence of risky health behaviors. One goal of the Affordable Care Act (ACA) was to increase preventive care and improve health behaviors by expanding access to health insurance. This paper estimates how the ACA's state-level expansions of Medicaid in 2014 affected these outcomes. Using data from the Behavioral Risk Factor Surveillance System, and a difference-in-differences model that compares states that did and did not expand Medicaid, we examine the impact of the expansions on preventive care (e.g. dental visits, immunizations, mammograms, cancer screenings) and risky health behaviors (e.g. smoking, heavy drinking, lack of exercise, obesity). We find evidence consistent with increased use of certain forms of preventive care such as dental visits and cancer screenings but little evidence of changes in health behaviors and in particular no evidence of ex ante moral hazard (i.e., no evidence that risky health behaviors increased in response to health insurance coverage). The Medicaid expansions also resulted in modest improvements in self-assessed health and decreases in the number of work days missed due to poor health.

Kosali Simon
School of Public and Environmental Affairs
Indiana University
Rm 443
1315 East Tenth Street
Bloomington, IN 47405-1701
and NBER
simonkos@indiana.edu

John Cawley
2312 MVR Hall
Department of Policy Analysis and Management
and Department of Economics
Cornell University
Ithaca, NY 14853
and NBER
JHC38@cornell.edu

Aparna Soni
Business Economics and Public Policy
Kelley School of Business
Indiana University
1309 East Tenth Street
Bloomington, IN 47405
apsoni@indiana.edu

1. Introduction

In the United States and other developed countries, participation in risky health behaviors and failure to utilize preventive care are major contributors to greater morbidity, larger health disparities, higher medical care costs, and increased mortality (NCHS, 2015; US PSTF, 2014; NPC, 2011; US DHHS, 2000). Examples of relevant preventive care include flu vaccinations and screening for sexually transmitted infections, and examples of relevant risky health behaviors include physical inactivity and tobacco use (NPC, 2011). The need to increase preventive care and improve health behaviors has been emphasized by the U.S. Surgeon General (US DHHS, 2014; US DHHS, 2010a), the U.S. Preventive Services Task Force (US Preventive Services Task Force, 2005), the National Prevention Council (NPC, 2011), and the Healthy People 2020 initiative (US DHHS, 2010b, 2000). Particular emphasis has been put on improving such behaviors among low-income and otherwise disadvantaged populations, with the goal of reducing health disparities (e.g. NPC, 2011; US DHHS 2010b).

Health insurance is seen as an important mechanism for increasing use of preventive care and improving health behaviors; in fact, this was a stated rationale of the Patient Protection and Affordable Care Act (ACA) of 2010 (ASPE, 2015; US DHHS, 2016). The ACA mandates that health insurance plans, including Medicaid, cover preventive services without cost-sharing as part of the “10 Essential Benefits” package; the law also expands insurance to vulnerable populations, increasing their contact with the healthcare system and exposing them to healthcare professionals’ advice regarding healthy behaviors (A Healthier America, 2013). In this paper we examine whether the insurance expansions that took place under the ACA had their intended effects of increasing preventive care and improving health behaviors.

The ACA had many insurance expansion components; the one that we examine concerns the Medicaid program. The ACA originally required that all states expand Medicaid to all adults whose income was below 138% of the federal poverty line (FPL). However, in 2012 the Supreme Court allowed states to opt out of this requirement, with the result that only 27 states had expanded Medicaid by the end of 2014: two in 2011, four in 2012, and 21 in 2014 (Sommers, Kenney, & Epstein, 2014; Kaiser Family Foundation 2015). In these expansion states, Medicaid was made available to a key demographic group that was previously largely ineligible for any public health insurance: low-income, non-elderly, non-disabled childless adults (henceforth referred to as “childless adults”).² This is the group that we examine in this study.

In theory, the impact of gaining health insurance coverage on preventive care and health behaviors is ambiguous. The law of demand implies that a reduction in the out-of-pocket cost of preventive care should result in increased utilization. However, consumers may not be very sensitive to the price of preventive care; the RAND Health Insurance Experiment estimated that the price elasticity of demand for preventive care is in the range of -0.17 to -0.43 (Newhouse et al., 1993; Aron-Dine et al., 2013; Ringel et al., 2002). Reasons that the demand for preventive care may be relatively inelastic include long wait times at provider offices (Anderson, Camacho, & Balkrishnan, 2007), the discomfort associated with screenings such as mammograms and colonoscopies (Takahashi, et al., 2005), and the anxiety associated with screenings for conditions such as cancer or HIV (Lerman et al. 1993, Kash, et al., 1992). The RAND Health Insurance Experiment found that, even in the zero-copay (free) plan, the majority of adult males used no preventive services at all for the entire three-year period of the study; thus, the authors note that

² The eligibility of parents was also affected, but to a much lesser degree because of a pre-existing avenue for access to Medicaid. Among expansion states, parents’ eligibility increased from a median 100% FPL to 138% FPL whereas childless adults’ eligibility increased from a median 0% to 138% (Artiga & Cornachione, 2016).

even with free care, uptake of preventive services can fall far short of accepted standards (Newhouse et al., 1993, p. 178-180).

Likewise, the impact of health insurance on health behaviors is ambiguous. Any increase in contact with health care providers resulting from health insurance could reduce risky health behaviors. Primary care physicians are recommended to screen their patients for tobacco use, alcohol misuse, obesity, and HIV infection, and to provide behavioral counseling for persons engaged in risky health behaviors (U.S. Preventive Services Task Force, 2014). On the other hand, insurance coverage may cause ex-ante moral hazard; patients have less incentive to reduce their risky health behaviors because they no longer pay the full financial cost of their future illness (Ehrlich & Becker, 1972). For example, Dave & Kaestner (2009) find that Medicare increases the probability of daily alcohol consumption among men. However, health insurance does not reduce the non-financial consequences of illness, such as physical pain and suffering, which could limit the extent of ex-ante moral hazard (Ehrlich & Becker, 1972).

One final mechanism by which health insurance may affect these outcomes is the income effect. The newly-insured may allocate some of the funds they would have otherwise devoted to health care towards risky health behaviors (e.g. cigarettes or eating more) or towards health improvements. Evidence of income effects on health behaviors is mixed. To take the example of weight, studies have found that income increases BMI among lower-income youths (Akee et al., 2013) and lower-income women (Schmeiser, 2009) but not among lower-income men (Schmeiser, 2009) or Social Security recipients (Cawley, Moran, & Simon, 2010). In summary, health insurance coverage may affect preventive care and health behaviors through multiple channels; the net impact is theoretically ambiguous and thus is ultimately an empirical question.

Although studies have looked at the impact of the 2014 Medicaid expansions on insurance coverage, hospital stays, and diagnoses of diabetes and cholesterol (Wherry & Miller, 2016), this paper is the first to estimate the impact of the 2014 Medicaid expansions on health behaviors. More broadly, it contributes to the growing literature on the effects of the ACA, and on the effects of health insurance in general. The existing studies of the 2014 expansions have found that they increased insurance coverage and improved access to care (ASPE, 2015; Sommers et al., 2015; Shartzler, Long, & Anderson, 2015; Sommers, Blendon, & Orav, 2016; Kaestner et al., 2015; Wherry & Miller, 2016) with no discernible effects on labor market outcomes (Gooptu, et al., 2016; Kaestner, et al., 2015).

There are also studies of the state Medicaid expansions that took place prior to 2014. These “early” Medicaid expansions increased insurance coverage (Sommers, Kenney, & Epstein, 2014), lowered mortality, reduced cost barriers to care, and improved self-assessed health (Sommers et al., 2012). There is little evidence as yet on the behavioral health impact of these early Medicaid expansions.

While this paper is the first to study the effect of the 2014 Medicaid expansions on preventive care and health behaviors, prior research has studied the effects on these outcomes from earlier expansions of health insurance, such as the ACA’s mandate to cover young adults (Barbaresco, Courtemanche, & Qi, 2015), the Oregon Medicaid experiment (Finkelstein et al., 2012), the Massachusetts healthcare reform of 2006 (Van Der Wees, Zaslavsky, & Ayanian, 2013; Courtmanche & Zapata, 2014; Miller, 2012), the Medicaid and CHIP expansions for children and low-income parents in the 1990s (Epstein & Newhouse, 1998), and the RAND health insurance experiment (Newhouse et al., 1993; Brook et al., 1983). In the conclusion, we compare our results with those of these prior studies.

We contribute to the literature on insurance and health behaviors in three ways. First, we add to the growing body of research on one of the largest insurance expansions to date – the ACA Medicaid expansion. Second, we provide the first evidence of the effect of these expansions on preventive care and health behaviors. Much of the current research on the ACA Medicaid expansions studies their impact on use of acute care rather than preventive care. This is likely due to the ready availability of large-scale administrative datasets on hospital discharges. However, a key motivation expressed by policy-makers for the expansions is the potential for cost savings from increased preventive care and improved health behaviors. We examine an extensive set of measures of each, such as routine checkups, flu shots, HIV tests, dental visits, cancer screenings, smoking, exercise, heavy drinking, and obesity. In addition, we examine the effect on insurance coverage and perceived access to care (which are likely preconditions for improvements in preventive care and health behaviors) and the ultimate outcome of self-assessed health.

Third, we examine the impact of insurance coverage for a novel population. Earlier insurance expansions primarily benefitted children, pregnant women, and low-income parents. The 2010 dependent insurance provision of the ACA affected young adults whose parents had access to employer-sponsored insurance; this group was likely to be higher income than the Medicaid eligible population. In contrast, the 2014 Medicaid expansions that we study primarily benefitted low-income childless adults, which is a population with reduced eligibility for other public welfare programs and higher risk for poor health behaviors and outcomes. Therefore, the low-income population we study may respond differently than those affected by earlier expansions.

The outline of the paper is as follows. In section 2, we describe our data. In Section 3, we describe our difference-in-differences model. Section 4 presents the empirical results, and Section 5 concludes.

2. Data: Behavioral Risk Factor Surveillance System (BRFSS)

Our primary data source is the Behavioral Risk Factor Surveillance System (BRFSS), an annual telephone survey conducted by the Centers for Disease Control and Prevention and state governments to collect information on health behaviors, insurance coverage, and health outcomes. The survey is conducted every month in all 50 states and the District of Columbia through random-digit dialing. The survey is designed to be representative of the non-institutionalized adult population in the United States.

The BRFSS has several advantages that make it useful for our analysis. First, it includes many outcome variables of interest: insurance status, access to care, preventive care usage, health behaviors, and self-assessed health. It also includes state identifiers and relevant demographic characteristics. The large sample size of nearly 500,000 each year ensures that there is a substantial sample of the people most affected by the recent Medicaid expansions: low-income childless adults. The BRFSS also has its limitations; prior to 2014 it does not record the source of insurance, so while we know whether people have health insurance in those earlier years, we do not know if it is Medicaid. In addition, the BRFSS is a repeated cross-section, so it is not possible to observe transitions from uninsured to coverage through Medicaid. Despite these limitations, the dataset's size, comprehensiveness, and timely availability offer an

important opportunity to learn about the early effects of the Medicaid expansions on preventive care and health behaviors.³

For our primary analysis, we use the BRFSS data for 2012-2014. The BRFSS provides information about date of interview, so our unit of time is quarter; using quarter rather than year allows us to examine pre-trends in more detail, which is important because our difference-in-differences model (explained in the next section) relies on the assumption of parallel trends between the expansion and non-expansion states. We restrict our analysis to 2012 and later due to a change in BRFSS weighting methodology in 2011. Thus, we have eight quarters of pre-expansion data (Q1 2012 through Q4 2013) and four quarters of post-expansion data (Q1 2014 through Q4 2014). We acknowledge that we have limited data from after the expansion, but the year of data that exist provide us with early evidence on the short-run effects of the Medicaid expansion.

We restrict the BRFSS sample to the group targeted by the Medicaid expansion: low-income childless adults. The criteria for inclusion in the estimation sample are that respondents must be aged 19-64, have no children age 18 years or younger, and report household incomes below 100% of the FPL.⁴ Although BRFSS records income only in categories, household income is reported in \$5,000 to \$7,500 brackets at the lower income levels and the specific cutoffs of \$10,000 and \$15,000 match fairly well with the federal poverty level for single individuals and families of two individuals (which are the relevant sizes of families for childless

³ Another advantage of the BRFSS is that at 49%, its response rate is relatively high compared to other surveys such as the Gallup Healthways Wellbeing Index which has a response rate of only 5-10 percent. The high response rate reduces the risk of sample selection bias. Although other datasets such as the National Health Interview Survey (NHIS) have higher response rates, their sample sizes are much lower than the BRFSS. The NHIS sample size, for example, is about one-sixth the size of the BRFSS, and may not allow for the subsample analysis we are able to conduct using the BRFSS.

⁴ Approximately 12.5% of observations in our sample are missing income data (response was “unsure,” “refused to answer,” or otherwise missing); we dropped these observations for our analysis.

adults). We use the upper threshold of the BRFSS income category as well as the reported household size to assign each respondent a percentage of the FPL. For example, in 2012, the federal poverty level for a family of 2 was \$15,930. Respondents who had a household size of 2 and income in the “less than \$10,000” were coded as 63% FPL ($\$10,000/\$15,930$), income in the “\$10,000-\$15,000” category were coded as 94% FPL ($\$15,000/\$15,930$), and income in the “\$15,000-20,000” category were coded as 126% FPL ($\$20,000/\$15,930$). After assigning an FPL value for each observation, we dropped any observations with FPL values greater than 100%. Although the Medicaid expansion was available for adults up to 138% FPL, we only examine those under 100% FPL because adults with income 100%-138% FPL in non-expansion states received an insurance expansion treatment – they became eligible for exchange subsidies in 2014.⁵

We exclude veterans and pregnant women from our sample, as these groups were previously eligible for public insurance under different and more generous eligibility criteria than other adults. Ideally we would exclude disabled adults from our sample as well, because most of those who receive disability income and were below the poverty level were categorically eligible for Medicaid in most states even before 2014. However, the BRFSS does not have a consistent way to identify the disabled, and so we are unable to exclude them from our analysis; this should bias downward our estimates of behavioral responses to the expansion.

⁵ Kaestner et al. (2015) use low education to identify those eligible for Medicaid because the ACA could affect income through the mechanism of health. We chose to use low income to define Medicaid eligibility, given that there has been no detectable labor market impact of the Medicaid expansions (Gooptu et al., 2015), and because income and education are only weakly correlated in the BRFSS data; e.g. among non-elderly, childless adults earning under the poverty line in the BRFSS in 2012, only 21% reported education less than high school. Furthermore, only 31% of those with education less than high school reported that their income was below the poverty level. As a robustness check later in the paper, we use low education rather than low income to define eligibility for Medicaid.

In order to focus on treatment and control groups of states that are as “clean” as possible, we drop the 4 states plus DC that enacted the ACA Medicaid expansion in 2011-12 (CA, CT, MN, WA and DC), the 7 states that partially expanded Medicaid to childless adults before 2014 (AZ, DE, HI, IA, MA, NY, and VT), the 2 non-expansion states that made comprehensive insurance coverage available to childless adults through alternate programs (ME and WI), and the 1 state that expanded Medicaid in August 2014 (NH). Our final categorization of states is as follows:

- Our treatment group consists of 14 states that expanded Medicaid in 2014 and had little or no prior eligibility for childless adults: AR, CO, IL, KY, MD, MI, NJ, ND, NM, NV, OH, OR, RI, and WV.
- Our control group consists of 22 states that did not expand Medicaid as of 2014 and had little or no prior eligibility for childless adults: AL, AK, FL, GA, ID, IN, KS, LA, MS, MO, MT, NE, NC, OK, PA, SC, SD, TN, TX, UT, VA, and WY.
- We exclude from our analysis 14 states plus DC that had partial Medicaid expansions for childless adults before 2014 and therefore experienced less change due to the ACA (AZ, CA, CT, DE, DC, HI, IA, ME, MA, MN, NH, NY, VT, WA, and WI). However, as a robustness check later in the paper we add these states to the treatment group, because childless adults in those states did experience a positive (through smaller) increase in eligibility.

For more information on the categorization of states, and the details of the expansions, see Table 1.

[Insert Table 1 Here]

Our outcomes of interest are categorized into five groups. When we have multiple measures for the same category of outcome, we create an index variable that reflects all of the measures in that category. We briefly describe the outcomes below; Appendix A provides additional details on the definitions of the variables and the language of the BRFSS questions on which they are based.

Insurance Coverage. We first assess the impact of the Medicaid expansion on insurance status, because any impact of the expansion on health behaviors and preventive care is assumed to operate through changes in insurance coverage. Insurance is coded as a binary variable equal to 1 if the respondent answered yes to having any form of healthcare coverage, 0 if the respondent answered no, and missing if the respondent was unsure or refused a response.

Access to care. We examine access to care because we see it as another important mechanism for any impacts on preventive care or health behaviors. Our two measures of access to care are: 1) an indicator variable for whether the subject has a primary care physician; and 2) an indicator variable for whether the subject answered “no” to the question, “Was there a time in the past 12 months when you needed to see a doctor but could not because of cost?” Each is treated as a separate outcome, and we also create an index variable that equals one if either the subject has a primary care physician or replied that cost was not a barrier to care.

Preventive care. We construct binary variables for having received a routine checkup in the past year, a flu vaccination (shot or spray) in the past year, an HIV screening ever, and a dental visit in the past year.⁶ Certain types of preventive care are relevant only for women: whether received a pap test in the past year (recommended for women aged 21 and older), a

⁶ Most of the ACA expansion states only provide “limited” dental coverage for adults; see Buchmueller, Miller, and Vujicic (2016) for details on state Medicaid dental provision generosity. Medicaid generally does not cover major restorative procedures like crowns, but the dental coverage provided in almost all of our 14 expansion states is generous enough to at least cover routine cleanings and inexpensive care; thus, it is plausible that the Medicaid expansion could affect whether childless adults visited a dentist at least once in the past year.

clinical breast exam in the past year (recommended for women aged 21 and older), and a mammogram in the past year (recommended for women aged 50 and older); see U.S. Preventive Services Task Force (2014). Data on dentist visits, cancer screenings index, clinical breast exams, Pap tests, and mammograms were not available for most states in BRFSS 2013, and so we drop the year 2013 only for these outcomes. We also constructed an index that measures the total number of such preventive care services (routine checkups, flu vaccination, HIV test, and dentist visits) an individual received in the past year. For women, we constructed an index for whether they received at least one recommended cancer screening (pap test, breast exam, or mammogram) for their age group.

Health behaviors. We examine six measures of health behaviors: 1) an indicator variable for whether the person has smoked in the past month; 2) an indicator for whether the person has engaged in heavy drinking (defined as two drinks per day for men and one drink per day for women) in the past month; 3) an indicator for whether the person has engaged in binge drinking (defined as having x or more drinks on one occasion, where $x=5$ for men and $x=4$ for women) in the past month; 4) an indicator for whether the person has participated in any physical activities or exercise in the past month; 5) body mass index or BMI (calculated as weight in kg divided by height in meters squared⁷; and 6) an indicator for whether the person is obese (i.e. $BMI \geq 30$); see Appendix A for more detail on the BRFSS questions on which these variables are based. We also create an index that equals one if the individual is a smoker, has not exercised in the past month, is a heavy drinker, is a binge drinker, or is obese.

⁷ The BRFSS collects only self-reports, not measurements, of weight and height, so BMI is likely underestimated (Cawley et al., 2015). Because weight is a dependent variable rather than independent variable, this error will not necessarily bias coefficients but it will increase the standard errors.

Self-assessed health. We examine four measures of self-assessed health: 1) the individual's self-rated health on a scale of 1 to 5; 2) the number of days in the past month that physical health was not good, reported by the respondent; 3) the number of days in the past month that mental health was not good, reported by the respondent; and 4) the number of days in the past month that the individual's poor health prevented usual activities such as work. In addition, we construct an index of number of unhealthy days that is the sum of days in the past month that the respondent had physical or mental health that was not good or missed work because of poor health, top-coded at 30.

We examine a large number of diverse outcomes. Following the literature (e.g. Barbaresco, Courtemanche, & Qi, 2015), we do not use multiple hypothesis test adjustments such as the Bonferroni adjustment. The Bonferroni adjustment is appropriate when, e.g., a large number of outcomes are used without preplanned hypotheses (i.e. data mining), or one is more interested in whether all tests are jointly not significant as opposed to being interested in the results of individual tests (Armstrong, 2014). Our outcomes are diverse but all are plausibly affected by health insurance coverage, and we are very much interested in the results of individual tests as opposed to a single test of whether we cannot reject *any* null hypotheses.

Our models control for the following regressors: indicator variables for marital status, age in years, employment status, gender, race/ethnicity, household income category, education, household size, and whether the individual is part of the BRFSS cell phone sample as opposed to the land line sample. Additionally, we control for the quarterly state unemployment rate, obtained from the Bureau of Labor Statistics, to account for possible different impacts of the 2012-14 economic recovery on different states.

3. Methods

We estimate difference-in-differences (DD) models that compare changes in outcomes in the treatment states to changes in the same outcomes in the control states. The sample consists solely of low-income childless adults, whose eligibility for Medicaid was most affected by the expansions. The “pre” period is 2012-13, and the “post” period is 2014. The treatment states are the 14 states that in 2014 newly expanded Medicaid to low-income childless adults, and the control states are the 22 states that have not yet expanded Medicaid to this population; see Table 1. For each of our outcome variables, we estimate the following DD regression:

$$Y_{ist} = \alpha + \beta(Treatment_s * Post_t) + \gamma X_{ist} + \eta UnempRate_{st} + \delta State_s + \vartheta Time_t + \varepsilon \quad (1)$$

where Y_{ist} represents a health-related outcome for individual i living in state s at time t , expressed as a quarter/year combination. For the binary outcomes, we estimate linear probability models because they typically give reliable estimates of average effects (Angrist & Pischke, 2008); however, as a robustness check, we also estimate these models as logits.

Treatment is a binary variable equal to 1 if the individual lives in a treatment state, and equals 0 if the respondent lives in a control state. *Post* is a binary variable equal to 1 if the time period is after the policy implementation (i.e. any quarter of 2014) and equals 0 if the time period is prior to the 2014 expansions (i.e., any quarter in 2012 or 2013). X is the vector of control variables: household income, education, gender, race, unemployment status, age, gender, marital status, household size, and cell phone sample indicator. *UnempRate* is a continuous variable measuring the state unemployment rate in a given quarter/year. *State* is a vector of state fixed effects, and *Time* is a vector of quarter/year-fixed effects. Standard errors are clustered by state.

Identification of the treatment effect relies upon the parallel trends assumption: that the control states are a good counterfactual for the treatment states; i.e. that in the absence of the

treatment, outcomes in the treatment states would have followed the same trend as those in the control states. If true, then the DD coefficient β identifies the effect of Medicaid expansions on the outcome.

The decision to expand Medicaid was controversial and highly politicized in many states (Jacobs & Callaghan, 2013). Given that more liberal states tended to expand while more conservative states chose not to expand, there may be violations of the parallel trends assumption that could cause bias. For this reason, we first assess the validity of the parallel trends assumption by comparing pre-treatment trends in outcomes in the treatment and control states. We do this by first visually assessing graphs of the trends. We then formalize the pre-trends test by estimating regressions using only data prior to the enactment of the law in 2014. We keep the same outcome variables on the left-hand side and the same control variables on the right-hand side, but our key independent variable now is an interaction between the linear time trend and the treatment group dummy instead of the usual DD variables.

Our main models are estimated for men and women pooled, but we also estimate models separately by sex. Past literature suggests that men and women are different in their levels of risk aversion and may respond differently to insurance coverage (Jianakoplos & Bernasek, 1998; Barbaresco, Courtemanche, & Qi, 2015).

For suggestive evidence regarding the validity of the identifying assumptions, we conduct several falsification tests. Specifically, we estimate the same models for populations whose eligibility for health insurance was unaffected in the 2014 Medicaid expansions: adults over age 65 (continually eligible for Medicare, with eligibility for Medicaid unchanged) and high-income adults (defined as adults with household income above 600% of the FPL and thus never eligible for Medicaid). Because the Medicaid eligibility of each of these two groups was not affected by

the 2014 expansions, we expect to find no effect of the expansions on their preventive care or health behaviors; if we find such effects, it would imply that the model is biased due to violations in the parallel trends assumption. Failure to find such effects is of course not proof that the parallel trends assumption is correct, but the failure to reject the null hypothesis of no effect provides some additional confidence in the approach.

Finally, we assess the robustness of the findings of the main model to numerous variations in the sample and model specification.

4. Empirical Results

Summary Statistics

We first compare, in Table 2, the sample means of our outcomes and selected control variables for the treatment and control groups, both before and after expansion. For most demographic variables displayed in Panel 1 of Table 2, the means are similar across the groups and over time. Although t-tests suggest that treatment and control states are significantly different in terms of mean age, education, marital status, and race/ethnicity, the differences tend to be small (e.g. less than a year of age, less than a third of a year of education) and we account for these differences by controlling for them in our regression models. The identifying assumption of the DD model does not concern equal means, but parallel trends; examining this assumption is the subject of the next subsection.

[Insert Table 2 here]

Plausibility of the Parallel Trends Assumption

We examine the visual evidence concerning parallel trends in Figure 1, which presents the trends in insurance coverage for our study sample, separately for the treatment and control groups.⁸ The vertical line on the left indicates Q4 of 2013, and the vertical line on the right indicates Q1 of 2014; thus, the Medicaid expansion of January 2014 happened in between the vertical lines. Figure 1 shows that the treatment and control states had similar trends in insurance coverage before the expansion. After the expansion, insurance coverage rises considerably in the treatment states relative to the control states, as one would expect. We provide graphs illustrating the trends in our other outcome variables in Appendix B. The other outcomes also exhibit similar pre-trends for the expansion and non-expansion states.

We more formally test for equality of the pre-expansion trends by estimating regressions using only data prior to the enactment of the law in 2014. If we were to find that preventive care and health behaviors were changing for the treatment group relative to the control group even before the policy change, that would suggest that the DD estimate is biased. Following Akosa Antwi, Moriya, and Simon (2015), we estimate a model keeping the same outcome variables on the left-hand side and the same control variables on the right-hand side, but our key independent variable now is an interaction between the linear time trend and the treatment group dummy instead of the DD variable. Results are presented in Table 3.

The first panel of Table 3 shows that the trends prior to the Medicaid expansions in insurance coverage are not significantly different between the treatment and control groups. Panels 2-5 report the results of the pre-expansion trend test for outcomes related to access to

⁸ We note that even prior to the Medicaid expansion, approximately 56% of childless adults in our treatment states and 52% of childless adults in our control states had some form of health insurance. Although the pre-2014 BRFSS does not provide us with the source of insurance, data from the American Community Survey and Current Population Survey suggest that this population was mostly covered by Medicaid or state-funded program, employer-sponsored coverage, or self-insurance. We also analyze source of insurance in BRFSS 2014 and find that among the control states, 31% were covered by Medicare, 29% by Medicaid or state-funded program, 16% by employer-sponsored insurance, and 15% through self-insurance.

care, preventive care, health behaviors, and self-assessed health. For the vast majority of outcomes, we cannot reject the null hypothesis of equal trends. These results, while not definitive, are reassuring evidence that the key assumption of the DD study design is satisfied for most of the outcomes. We do, however, find significantly different trends for three outcomes: routine checkups, number of preventive care services received (which is a function of routine checkups), and exercise. However, the pre-trend test indicates that routine checkups and number of preventive care services were *declining* in the expansion states relative to the control states, which is the opposite of the expected treatment effect; thus, any violation of the parallel trends assumption may bias the DD model against finding an effect of Medicaid expansion on these outcomes.

[Insert Table 3 here]

Baseline DD Model: Impact of Medicaid Expansion on Low-Income Childless Adults

Table 4 (column 2) presents the full results of our baseline DD model. Results are presented by category of outcome, with panel 1 presenting results on insurance coverage, panel 2 access to care, panel 3 results on preventive care, panel 4 health behaviors, and panel 5 overall health status.

Insurance. Table 4, panel 1 shows that the expansion of Medicaid eligibility in 2014 increased the probability that low-income childless adults had health insurance coverage by 15.5 percentage points or 28% from pre-expansion level. Table 4 also presents results separately by gender in columns 3 and 4. Among women, the probability of coverage rose 17.1 percentage points and among men it rose 14.2 percentage points; both are statistically significant, and the difference between the coefficients for men and women is not statistically significant.

Access to care. Table 4, panel 2 indicates that the Medicaid expansions increased overall access to care by 3.3 percentage points (or 4% from pre-expansion level). Specifically, the expansion reduced the proportion of adults who reported cost as a barrier to care by 2.7 percentage points or 7% from pre-expansion level. The effect varied significantly by sex; among men, the probability of reporting cost as a barrier to care fell by 5.2 percentage points, but for women the point estimate is small and positive (0.1 percentage points), and not statistically significant. The Medicaid expansion did not affect the probability of having a personal doctor for either men, women, or the pooled sample.

Preventive care. Table 4, panel 3 indicates that the Medicaid expansion significantly increased the probability of a dentist visit in the past year by 8.4 percentage points (20% rise from pre-expansion). The effect differs by sex; it rose 11.0 percentage points for women compared to 5.8 percentage points for men, a difference that is statistically significant. Although the cancer screening index for women did not significantly change, the clinical breast exam component rose by 5.8 percentage points (14%), and the probability of a mammogram rose 6.8 percentage points (16%). The expansion had no detectable effect on flu shots, HIV tests, or Pap tests. Despite the fact that the number of preventive services and routine doctor visits were decreasing in the treatment states prior to the expansions, the DD model implies that the expansions increased those significantly; e.g. the probability of a routine checkup rose 5.9 percentage points or 10%.

Health behaviors. Table 4, panel 4 indicates that there was no detectable impact of the expansion on most health behaviors, including smoking participation, binge drinking, exercise, BMI, or obesity. The exception is a rather large and statistically significant estimated effect on the probability of heavy drinking, suggesting that expansion reduced this behavior by 2.5

percentage points (31%); the impact is concentrated among the female population. The magnitude of the reduction in heavy drinking (nearly a third) is so large as to be implausible.

Self-assessed health. Table 4, panel 5 indicates that the expansion was associated with small improvements in self-rated health (specifically, an increase of 0.1 point on a 5-point scale, or a 3% rise from pre-expansion level). The number of unhealthy days did not decline significantly, although the number of days that poor health prevented work declined by 0.8 (8%). There is no detectable effect of the expansion on days of poor physical health for the pooled sample, but among men this falls by 1.1 days (12.5%).

[Insert Table 4 Here]

Falsification Tests

We conduct falsification tests using two populations whose eligibility for Medicaid was unaffected by the expansion: adults over age 65 and high-income adults (defined as above 600% FPL). Results of these falsification tests are provided in Table 5. As expected, the Medicaid expansion had no impact on the probability of coverage or access to care for these populations. Panel 3 shows that the expansions had no impact on preventive care for individuals over age 65 (other than clinical breast exam) or high-income individuals (other than Pap tests). Panel 4 shows that the Medicare expansions were not associated with changes in health behaviors in these populations, with the exception that smoking rose slightly among the over-65 population (0.7 percentage points) and that obesity rose slightly among the wealthy population, both of which are the opposite sign of the expected effect of the expansion. In panel 5 concerning health status, most of the outcomes are not significantly affected, except that the number of days that mental health was not good increased for high-income individuals, which is again the opposite sign of the expected effect of the expansion on treated individuals. In summary, most of the outcomes

are not significantly associated with the Medicaid expansions for these populations; the associations that exist tend to be of the opposite sign. Overall, the falsification tests yield no evidence that the improvements seen for the low-income childless adults targeted by the expansions are due to differences in trends or other potential sources of bias.

[Insert Table 5 Here]

Sensitivity Analyses

We examine the sensitivity of our main results to modifications of the sample or model. Our first set of sensitivity analyses is presented in Table 6A. First, we estimate a logit model for our binary outcomes rather than the linear probability model used in our baseline model. The statistical significance of the results (shown in column 1 of Table 6A) is quite similar to our main results, with the exception that the logit model also suggests that the expansion increased the good access to care index by 3.6 percentage points (or 4%).

Second, we estimate our models without using BRFSS sample weights. Solon et al. (2015) question the use of sample weights in research that seeks to estimate causal effects, and recommend reporting both weighted and unweighted estimates. The results (in column 2 of Table 6A) are very similar to the main results; the notable change is that the expansion has a significant effect on a few additional outcomes: whether the respondent reports having a personal doctor (increases by 2.1 percentage points or 3%) and the number of days in the past month that mental health was not good (decreases by 0.7 days or 8%). These are both consistent with the overall conclusion arising from the main models, that the expansions improved access and health.

Third, we explore adding a linear state specific time trend (in quarters). We exclude state-specific time trends from the main model because they may pick up the effect of the policy and not just preexisting trends (see Wolfers, 2006). The results, in column 3 of Table 6A, are weaker, because controlling for state-level trends reduces the variation available to identify state policy change effects, but several main results still hold (increases in routine checkups and improvement in self-rated health).

Fourth, we exclude the first two quarters of 2014, because these may have been transitional periods, during which people had not yet received coverage or care, or perhaps there was not yet time for effects to be manifested in the outcomes we examine. The results, in column 4 of Table 6A, indicate that the expansions had a larger increase in health insurance coverage (consistent with the first half of 2014 being transitional) with a significant increases in dental visits, significant reductions in the probability of heavy drinking, but the impact on self-rated health is smaller and not statistically significant. This last finding is surprising, as we would expect any impact of health insurance coverage on health to increase over time.

Fifth, we estimate the DD model using only the four states that had the lowest pre-2014 insurance rates (IL, AR, NJ, and NV) as our treatment group and keep the original 22 non-expansion states as our control group. The results are generally robust (e.g. increases in routine doctor visits, increases in dental visits, reduction in heavy drinking, reduction in days that poor health prevented work), although there is also a significant increase in smoking and the unhealthy behavior index.

Another set of sensitivity analyses is included in Table 6B. In column 1 of Table 6B, we report results from models in which we include parents in our sample (which previously included only childless adults). Low-income parents did experience an increase in Medicaid eligibility,

but it was much smaller than that enjoyed by low-income childless adults. In column 2 of Table 6B, we report estimates from a model in which we include in the treatment group the ACA expansion states in which low-income childless adults had partial eligibility for Medicaid prior to 2014. Such states did experience an increase in eligibility among low-income childless adults as a result of the 2014 expansions, but less of course than the states in which this group was not at all eligible for Medicaid. With the addition of these states, the sample now includes all 50 states plus DC. In both of these sensitivity analyses, the results are generally consistent with our main results. The expansion is associated with a significant increase in health insurance coverage, an increase in preventive services received, and an improvement in self-rated health. The point estimates are smaller, and fewer results are statistically significant, when parents are included in the sample, which makes sense because they experienced less of an increase in eligibility so there should not be as much of a behavioral change in response.

As a final robustness check, we define eligible childless adults using low education (less than 12 years of education) rather than low income. The results, shown in column 3 of Table 6B, indicate that the increase in insurance coverage is much smaller for the low-education sample than the low-income sample (4.5 percentage points compared to 15.5 percentage points), and as a result the behavioral changes are smaller and virtually none are statistically significant. This is consistent with our assessment that in the BRFSS low education is not a strong predictor of low income, and thus of Medicaid eligibility (see footnote 5).

In summary, the finding that the 2014 Medicaid expansions increased preventive care and improved self-rated health is robust to a wide variety of modifications of the sample and the model specification. The models also consistently yield little evidence of any changes in risky health behavior, other than a reduction in heavy drinking.

[Insert Tables 6A and 6B Here]

5. Conclusion

The ACA, motivated in part by concern about low use of preventive care and high engagement in risky health behaviors, sought to improve these outcomes by expanding Medicaid. This paper provides early evidence on the impact of Medicaid expansions in 14 states in 2014, focusing on the low-income childless adults who benefited from the expansions. Our particular contribution is that we provide the first evidence of the impact of these expansions on preventive care and health behaviors.

Results of difference-in-differences (DD) models indicate that the expansions increased certain types of preventive care, particularly dental visits (20%), breast exams (14%), and mammograms (16%). The fact that these increases were experienced by low-income individuals suggests that these expansions reduced health-related disparities, which is a major goal of public health policy in the U.S. (e.g. CDC, 2016; NPC, 2011; US DHHS 2010b). We find little evidence that the expansions affected risky health behaviors such as smoking, lack of exercise, or obesity. There is some evidence that it may have reduced the probability of heavy drinking, but the magnitude of the reduction (31%) may be too large to be plausible. This study is also the first to find that the 2014 Medicaid expansions improved self-rated health (3%) and reduced health-related job absenteeism (8%).⁹ Although the magnitude of the point estimates are somewhat sensitive to changes in the sample or model specification, the overall conclusions listed above are generally robust. These new findings concerning preventive care and health behaviors complement earlier research that found that the 2014 Medicaid expansions led to increases in

⁹ By combining the results for insurance with those for other outcomes, we are able to calculate elasticities of health behaviors with respect to insurance; these are provided in Appendix C.

overnight hospital stays and diagnoses of diabetes and high cholesterol (Wherry and Miller, 2016).

The DD models also confirm that the expansions significantly increased the probability that the targeted population had health insurance, and decreased the probability that cost was a barrier to their care; this is consistent with several other recent studies of the 2014 Medicaid expansions (ASPE, 2015; Sommers et al., 2015, Shartzler, Long, & Anderson, 2015; Sommers, Blendon, & Orav, 2016; Kaestner et al., 2015; Wherry & Miller, 2016).¹⁰

Our results are consistent with studies of the effects of earlier expansions of health insurance (i.e., not the 2014 Medicaid expansions but earlier extensions of health insurance, whether Medicaid or other types) on preventive care utilization, access to care, and health outcomes. The literature almost unanimously has found that insurance expansions improve access to medical care (Finkelstein et al., 2012; Miller, 2012). Other studies have also found positive impacts on preventive care utilization; for example, Finkelstein et al. (2012) examines data from the Oregon Medicaid experiment and finds that Medicaid expansion led to a higher probability of receiving cholesterol checks, blood tests, mammograms, and Pap tests. Van Der Wees, Zaslavsky, & Ayanian, (2013) exploits the 2006 Massachusetts healthcare reform and find a significant increase in the usage of Pap tests, colonoscopies, and cholesterol screenings. Miller (2012b) also finds that the Massachusetts reform resulted in increased probability of getting an annual check-up among children.

¹⁰ Few past studies examine the causal impact of the 2014 Medicaid expansion on the insurance rate of low-income childless adults specifically, and therefore it is difficult to place in context our result that the expansion caused a 15.5 percentage point increase in this population's insurance rate. In order to make our result more comparable to past studies, we estimate our model on an alternate population that has been more commonly used in the ACA literature thus far: all low-income adults (including parents and pregnant women). We find that in this population, the DD coefficient on insurance is 0.098 (implying a 9.8 percentage point increase in insurance rate resulting from expansion). This result is in line with DD estimates using alternate data sources (Sommers, Blendon, & Orav, 2016; Wherry & Miller, 2016).

There are inconsistent results in the literature regarding the effect of health insurance coverage on health. While some studies find that insurance expansions result in increased self-reported health (Sommers, Baicker, & Epstein, 2012; Finkelstein et al., 2012; Barbaresco, Courtemanche, & Qi, 2015), others have found little evidence of improved health. In particular, Wherry and Miller (2016), which uses a similar identification strategy (DD models) to study the impact of the 2014 Medicaid expansion, does not find any significant impact of the expansion on self-assessed health. In contrast, we find that the expansion improved self-rated health and reduced the number of days that poor health prevented work; the latter is more robust than the former.

We also contribute to the literature on the impact of health insurance coverage on ex ante moral hazard. Compared to insurance for events that have solely financial costs, health insurance may not lead to as much ex ante moral hazard because the insured individual would still endure the pain and suffering of illness, and pay the opportunity cost of time spent seeking treatment and recovering (Ehrlich & Becker, 1972).

The extent of ex ante moral hazard is important because it increases the deadweight loss associated with negative externalities that are due to smoking, sedentary lifestyles, and obesity that operate through the health insurance system. Specifically, if health insurance coverage leads to more smoking, less exercise, and more obesity, then the deadweight loss of the externalities in medical care costs from those activities is even greater (Bhattacharya & Sood, 2011; Bhattacharya & Sood, 2007). Our models yield no evidence that health insurance coverage increases smoking, increases heavy or binge drinking (in fact, we find that it decreases heavy drinking), decreases exercise, or increases obesity; thus, we find no evidence of moral hazard in those activities associated with health insurance.

The previous empirical literature is mixed in whether it finds evidence of such moral hazard. Some of the earlier evidence was also based on Medicaid. The randomized experiment in Oregon found that Medicaid coverage had no statistically significant impact on the probability of obesity, although the confidence intervals were very wide (Baicker et al., 2013). In contrast, two studies that exploit the 1990s state Medicaid expansions as natural experiments find evidence that health insurance coverage raises BMI (Kelly & Markowitz, 2009; Bhattacharya & Sood., 2011).

There is also evidence on ex ante moral hazard for health insurance programs other than Medicaid. Barbaresco, Courtemanche, and Qi (2015) examine the effect of the ACA's dependent care provision and estimate that health insurance coverage lowers BMI but increases risky consumption of alcohol. Courtemanche and Zapata (2014) examine the Massachusetts healthcare reform and find that health insurance coverage reduced BMI but did not affect smoking or physical activity. Dave and Kaestner (2009) examine those who newly qualify for Medicare and find that, controlling for employment status and number of doctor visits, gaining Medicare coverage reduced vigorous physical exercise and increased daily drinking and smoking, all among men. Other research on Medicare receipt confirmed a reduction in physical activity but found no clear effect on alcohol consumption or smoking (De Preux, 2011). The RAND Health Insurance Experiment found no evidence that *generosity* of health insurance (i.e. the intensive rather than extensive margin of coverage) had an impact on weight, physical activity, smoking, or alcohol consumption (Newhouse, 1993; Brook et al., 1983). The findings from this paper do not fully resolve this debate, but do add further weight to the body of research that finds no evidence that health insurance coverage leads to ex ante moral hazard in the form of increased risky health behaviors.

Comparisons with the earlier literature are complicated by the fact that the population of low-income childless adults treated by the 2014 Medicaid expansions are quite different from those treated by the ACA's young adult mandate, the 2006 Massachusetts health care reform, Medicare, and the RAND Health Insurance Experiment. The income effect of insurance access presumably is larger for the relatively lower-income group that we study. However, it is also possible that because low-income populations have greater access to charity care that their quantity of care demanded may not rise as much as otherwise.

We acknowledge the limitations of our analysis. The BRFSS is a repeated cross-section, so we cannot observe changes in specific individuals' behavior after gaining health insurance the way we could in a panel dataset. The income reported in BRFSS is categorical rather than continuous, so we may misclassify the Medicaid eligibility of some childless adults. Prior to 2014, BRFSS does not publish the source of individuals' health insurance, so we are unable to observe which low-income childless adults are covered by Medicaid after the expansion. However, prior studies of the 2014 expansions have verified that the insurance gains among low-income childless adults are due to Medicaid (Sommers, et al., 2015; Shartzler, Long, & Anderson, 2015; Sommers, Blendon, & Orav, 2016; Kaestner et al., 2015). We have only four quarters (one year) of data from after the expansion, but the data that exist provide us with early information on the short-run effects of the expansions. Despite these limitations, this paper provides important early information about the effects of the 2014 Medicaid expansions on preventive care and health behaviors. As additional data become available in subsequent years, future research will be able to examine the longer-run impacts of these health insurance expansions.

Works Cited

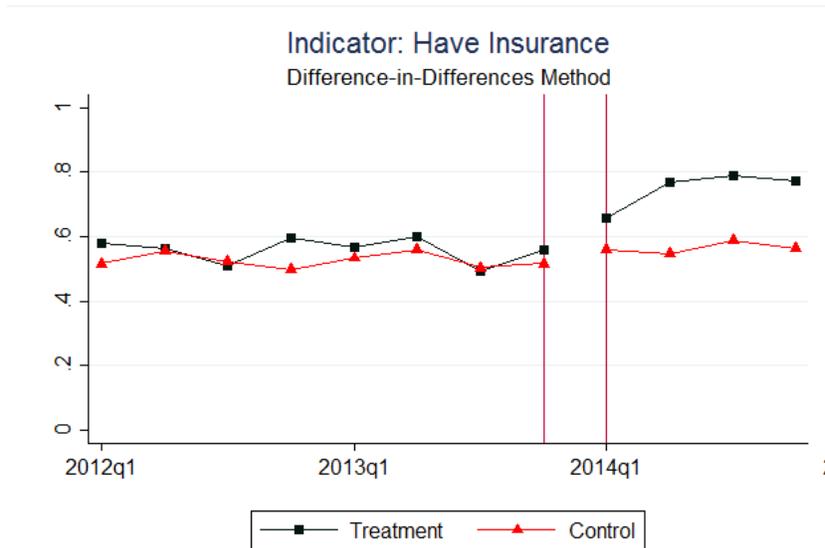
- Akee, R., Simeonova E., Copeland W., Angold A., & Costello, E.J. (2013). Young adult obesity and household income: Effects of unconditional cash transfers. *American Economic Journal: Applied Economics*, 5, 1-28.
- Anderson, R.T., Camacho, F.T., & Balkrishnan, R. (2007). Willing to wait?: The influence of patient wait time on satisfaction with primary care. *BMC Health Services Research*, 7, 31.
- Angrist, J.D., & Pischke, J.S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.
- Akosa Antwi, Y., Moriya, A.S. & Simon, K.I. (2015). Access to health insurance and the use of inpatient medical care; Evidence from the Affordable Care Act young adult mandate. *Journal of Health Economics*, 39, 171-187.
- Armstrong, R.A. (2014). When to use the Bonferroni Correction." *Ophthalmic and Physiological Optics*, 34(5): 502-508.
- Aron-Dine, A., Einav, L., & Finkelstein, A. (2013). The RAND health insurance experiment, three decades later. *Journal of Economic Perspectives*, 27, 197–222.
- Artiga, S., & Cornachione, E. (2016). Trends in Medicaid and CHIP eligibility over time. Kaiser Family Foundation. Retrieved April 20, 2016 from <http://kff.org/report-section/trends-in-medicaid-and-chip-eligibility-over-time-section-3-eligibility-trends-by-medicaid-expansion-status-2016-update/>.
- Assistant Secretary for Planning and Evaluation, U.S. Department of Health and Human Services. (2015). HHS strategic plan. Retrieved April 8, 2016, from <http://www.hhs.gov/about/strategic-plan/strategic-goal-1/>.
- Baicker, K., Taubman, S.L., Allen, H.L., Bernstein, M., Gruber, J.H., Newhouse, J.P., Schneider, E.C., Wright, B.J., Zaslavsky, A.M., Finkelstein, A.N., & Oregon Health Study Group. (2013). The Oregon experiment – effects of Medicaid on clinical outcomes. *New England Journal of Medicine*, 368, 1713–1722.
- Barbaresco, S., Courtemanche, C.J., & Qi, Y. (2015). Impacts of the Affordable Care Act dependent coverage provision on health-related outcomes of young adults. *Journal of Health Economics*, 40, 54-68.
- Bhattacharya, J., & Sood, N. (2007). Health insurance and the obesity externality. *Advances in Health Economics and Health Services Research*, 17, 279–318.
- Bhattacharya, J., & Sood, N. (2011). Who pays for obesity? *Journal of Economic Perspectives*, 25, 139–158.
- Brook, R.H., Ware Jr, J.E., Rogers, W.H., Keeler, E.B., Davies, A.R., Donald, C.A., Goldberg, G.A., Lohr, K.N., Masthay, P.C., & Newhouse, J.P. (1983). Does free care improve adults' health?: Results from a randomized controlled trial. *New England Journal of Medicine*, 309, 1426-1434.
- Buchmueller, T, Miller, S., & Vujicic, M. (2016). How do Providers Respond to Changes in Public Health Insurance Coverage? Evidence from Medicaid Adult Dental Coverage, *American Economic Journal*, forthcoming.
- Cawley, J., Maclean, J.C., Hammer, M., & Winfield, N. (2015). Reporting error in weight and its implications for estimates of the economic consequences of obesity. *Economics and Human Biology*, 19, 27-44.
- Cawley, J., Moran, J., & Simon, K.I. (2010). The impact of income on the weight of elderly Americans. *Health Economics*, 19, 979-993.

- Centers for Disease Control and Prevention. (2016). Strategies for Reducing Health Disparities – Selected CDC-Sponsored Interventions, United States, 2016. *Morbidity and Mortality Weekly Report*, 65(1, Suppl.): 1-70.
- Courtemanche, C.J., & Zapata, D. (2014). Does universal coverage improve health? The Massachusetts experience. *Journal of Policy Analysis and Management*, 33, 36-69.
- Damiano, P., Bentler, S.E., Momany, E.T., Park, K.H., & Robinson, E. (2013). Evaluation of the IowaCare program: Information about the medical home expansion. The University of Iowa Public Policy Center.
- Dave, D., & Kaestner, R. (2009). Health insurance and ex ante moral hazard: evidence from Medicare. *International Journal of Health Care Finance and Economics*, 9, 367–390.
- De Preux, L.B. (2011). Anticipatory ex-ante moral hazard and the effect of medicare on prevention. *Health Economics*, 20, 1056-1072.
- Ehrlich, I., & Becker, G.S. (1972). Market insurance, self-insurance, and self-protection. *Journal of Political Economy*, 80, 623-648.
- Epstein, A.M., & Newhouse, J.P. (1998). Impact of Medicaid expansion on early prenatal care and health outcomes. *Health Care Financing Review*, 19, 85-99.
- Finkelstein, A., Taubman, S., Wright, B., Bernstein, M., Gruber, J., Newhouse, J.P., Allen, H., Baicker, K., & The Oregon Health Study Group. (2012). The Oregon health insurance experiment: Evidence from the first year. *Quarterly Journal of Economics*, 127, 1057-1106.
- Gates, A., & Rudowitz, R. (2014). Wisconsin’s BadgerCare program and the ACA. The Henry J. Kaiser Family Foundation.
- Gooptu, A., Moriya, A.S., Simon, K.I. & Sommers, B.D. (2016). Reductions in 2014 Medicaid expansion did not result in significant employment changes. *Health Affairs*, 35, 111-118
- Heberlein, M., Brooks, T., Guyer, J., Artiga, S., & Stephens, J. (2011). Holding steady, looking ahead: Annual findings of a 50-state survey of eligibility rules, enrollment and renewal procedures, and cost-sharing practices in Medicaid and CHIP, 2010–2011. Kaiser Commission on Medicaid and the Uninsured.
- Jacobs, L.R., & Callaghan, T. (2013). Why states expand Medicaid: Party, resources, and history. *Journal of Health Politics, Policy and Law*, 38, 1023-1050.
- Jianakoplos, N.A., & Bernasek, A. (1998). Are women more risk averse? *Economic Inquiry*, 36, 620–630.
- Kaiser Family Foundation. (2013). Medicaid and the uninsured: Where are states today? Medicaid and CHIP eligibility levels for children and non-disabled adults. The Henry J. Kaiser Family Foundation.
- Kaestner, R., Garrett, B., Gangopadhyaya, A., & Fleming, C. (2015). Effects of ACA Medicaid expansions on health insurance coverage and labor supply. National Bureau of Economic Research Working Paper No. 21836. Cambridge, MA: National Bureau of Economic Research.
- Kash, K.M., Holland, J.C., Halper, M.S., & Miller, D.G. (1992). Psychological distress and surveillance behaviors of women with a family history of breast cancer. *Journal of the National Cancer Institute*, 84, 24-30.
- Kelly, I.R., & Markowitz, S. (2009). Incentives in obesity and health insurance. *Inquiry*, 46, 418–432.
- Lerman, C., Daly, M., Sands, C., Balshem, A., Lustbader, E., Heggan, T., Goldstein, L., James, J., & Engstrom, P. (1993). Mammography adherence and psychological distress among

- women at risk for breast cancer. *Journal of the National Cancer Institute*, 85, 1074-1080.
- Miller, S. (2012). The impact of the Massachusetts health care reform on health care use among children. *American Economic Review: Papers and Proceedings*, 102, 502-507.
- National Center for Health Statistics. (2015). *Health, United States, 2014: With special feature on adults aged 55–64*. Hyattsville, MD: Centers for Disease Control.
- Newhouse, J.P., & The Insurance Experiment Group. (1993). *Free for all? Lessons from the RAND health insurance experiment*. Cambridge, MA: Harvard University Press.
- Ringel, JS, Hosek SD, Vollaard, BA, Mahnovski S. 2002. *The Elasticity of Demand for Health Care. A review of the literature and its application to the military health system*. Santa Monica CA: RAND Corporation.
- Schmeiser, M. D. (2009). Expanding wallets and waistlines: The impact of family income on the BMI of women and men eligible for the earned income tax credit. *Health Economics*, 18, 1277-1294.
- Shartzter, A., Long, S.K., & Anderson, N. (2015). Access to care and affordability have improved following Affordable Care Act implementation; problems remain. *Health Affairs*, 10. <https://www.census.gov/content/dam/Census/library/publications/2015/demo/p60-253.pdf>.
- Solon G, Haider SJ, Wooldridge JM. 2015. What Are We Weighting For? *Journal of Human Resources*, 50, 301-316.
- Sommers, B.D., Baicker, K., & Epstein, A.M. (2012). Mortality and access to care among adults after state Medicaid expansions. *New England Journal of Medicine*, 367, 1025- 1034.
- Sommers, B. D., Buchmueller, T., Decker, S. L., Carey, C., & Kronick, R. (2013). The Affordable Care Act has led to significant gains in health insurance and access to care for young adults. *Health affairs*, 32, 165-174.
- Sommers, B.D., Kenney, G.M. & Epstein, A.M. (2014). New evidence on the Affordable Care Act: Coverage impacts of early Medicaid expansions. *Health Affairs*, 33, 78-87.
- Sommers, B.D., Gunja, M.Z., Finegold, K., & Musco, T. (2015). Changes in self-reported insurance coverage, access to care, and health under the Affordable Care Act. *Journal of the American Medical Association*, 314, 366-374.
- Sommers, B.D., Blendon, R.J., & Orav, E.J. (2016). Both the ‘private option’ and traditional Medicaid expansions improved access to care for low-income adults. *Health Affairs*, 35, 96-105.
- Takahashi, Y., Tanaka, H., Kinjo, M., & Sakumoto, K. (2005). Sedation-free colonoscopy. *Diseases of the Colon & Rectum*, 48, 855-859.
- Task Force on Community Preventive Services. (2005). *Guide to community preventive services*. New York: Oxford University Press.
- U.S. Department of Health and Human Services, Office of the Surgeon General. (2011). *National prevention strategy: America’s plan for better health and wellness*. Retrieved December 23, 2015, from <http://www.surgeongeneral.gov/priorities/prevention/strategy/report.pdf>.
- U.S. Department of Health and Human Services. (2000). *Healthy people 2000: Understanding and improving health*. Washington, DC: U.S. Government Printing Office.
- U.S. Department of Health and Human Services. (2010a). *The surgeon general's vision for a healthy and fit nation*. Rockville, MD: U.S. Department of Health and Human Services, Office of the Surgeon General.
- U.S. Department of Health and Human Services. (2010b). *Healthy people 2010: Understanding and improving health*, 2nd ed. Washington, DC: U.S. Government Printing Office.
- U.S. Department of Health and Human Services. (2014). *The health consequences of smoking*:

- 50 years of progress. A report of the surgeon general. Atlanta, GA: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, National Center for Chronic Disease Prevention and Health Promotion, Office on Smoking and Health.
- U.S. Department of Health and Human Services. (2016). Affordable Care Act rules on expanding access to preventive services for women. Retrieved April 17, 2016, from <http://www.hhs.gov/healthcare/facts-and-features/fact-sheets/aca-rules-on-expanding-access-to-preventive-services-for-women/index.html>.
- U. S. Preventive Services Task Force. (2014). The guide to clinical preventive services 2014: Recommendations of the U.S. preventive services task force. AHRQ Pub. No. 14-05158.
- Van der Wees, P.J., Zaslavsky, A.M., & Ayanian, J.Z. (2013). Improvements in health status after Massachusetts health care reform. *Milbank Quarterly*, 91, 663-689.
- Wherry, L., & Miller, S. (2016). Early coverage, access, utilization, and health effects associated with the Affordable Care Act Medicaid expansions: A quasi-experimental study. *Annals of Internal Medicine*.
- Wolfers, J. (2006). Did Unilateral Divorce Laws Raise Divorce Rates? A Reconciliation and New Results. *American Economic Review*, 96(5): 1802-1820.

Figure 1. Trends in Insurance Rates, Treatment vs. Control States



Notes: Source is BRFSS 2012-2014. Sample was restricted to include only non-elderly, <100% FPL, childless adults who are not pregnant and not veterans. Data are adjusted by BRFSS sample weight. States that offered at least some categorical eligibility for childless adults before 2014 are excluded from this analysis (See Table 1 for states in treatment, control, and excluded categories). The vertical lines indicate Q4 of 2013 and Q1 of 2014; thus, Medicaid expansions took place in between the two vertical lines.

Table 1. Classification of Treatment and Control States

	Treatment (expanded in 2014 and previously had little or no eligibility for childless adults)	Excluded (offered partial or full eligibility to childless adults before 2014)	Control (did not expand in 2014)
1	Arkansas ¹	Arizona ⁵	Alabama
2	Colorado ²	California ⁴	Alaska ¹³
3	Illinois	Connecticut ⁴	Florida
4	Kentucky	Delaware ⁶	Georgia
5	Maryland	District of Columbia ⁴	Idaho
6	Michigan ³	Hawaii ⁷	Indiana ¹³
7	New Jersey ⁴	Iowa ⁸	Kansas
8	North Dakota	Maine	Louisiana
9	New Mexico	Massachusetts ⁹	Mississippi
10	Nevada	Minnesota ⁴	Missouri
11	Ohio	New Hampshire ³	Montana ¹³
12	Oregon	New York ¹⁰	Nebraska
13	Rhode Island	Vermont ¹¹	North Carolina
14	West Virginia	Washington ⁴	Oklahoma
15		Wisconsin ¹²	Pennsylvania ¹³
16			South Carolina
17			South Dakota
18			Tennessee
19			Texas
20			Utah
21			Virginia
22			Wyoming

Note: This table shows the state classification used in our main specification as regards Medicaid eligibility for childless adults. These are mutually exclusive lists of states. We also estimate a model in which we do not exclude any states (see Table 5).

¹ Arkansas operated only a very limited limited-benefit premium-assistance program for childless adults who worked for small uninsured employers (ARHealthNetworks waiver) (Kaiser Family Foundation, 2013) prior to the ACA; because of this, we classified Arkansas as a 2014 expansion state

² Colorado had only very limited eligibility before 2014. Adults with income up to 10% FPL were eligible for Medicaid as of May 2012, and enrollment was capped to 10,000 adults (Kaiser Family Foundation, 2013).

³ Two Medicaid expansions became effective after January 1, 2014 (Michigan on 4/1/2014 and New Hampshire on 8/15/2014) but before 2015. We include Michigan in the treated group because its expansion was in effect for most of the year. We exclude New Hampshire because its expansion was not in effect for most of the year.

⁴ California, Connecticut, District of Columbia, Minnesota, New Jersey, and Washington elected to enact the ACA Medicaid expansion in 2010-11. However, New Jersey's early expansion only extended to 23% FPL while all the other states extended at least til 50% FPL (Sommers et al. 2014). Therefore we treat New Jersey as a treatment state.

⁵ Since 2000, Arizona offered Medicaid-equivalent benefits to childless adults with incomes below 100% FPL through a Section 1115 waiver program. Although the state closed the program to new enrollees in July 2011, any childless adults who were already enrolled as of July were permitted to stay on (Kaiser Family Foundation, 2013) and enrollment was approximately 75,000 in 2013.

⁶ In Delaware, childless adults with incomes up to 100% FPL were eligible for Medicaid benefits through the Diamond State Health Plan waiver (Kaiser Family Foundation, 2013).

⁷ In Hawaii, childless adults with incomes up to 100% FPL were eligible for the state's QUEST Medicaid managed care waiver program (Kaiser Family Foundation, 2013).

⁸ Under the IowaCare program, childless adults with income below 200% FPL were eligible for public health insurance since 2005. IowaCare provided coverage for most inpatient and outpatient services, including preventive care. Those with income below 150% FPL were not required to pay a premium (Damiano et al., 2013).

⁹ Massachusetts implemented reforms to expand insurance coverage to low-income adults in 2006 (Kaiser Family Foundation, 2013).

¹⁰ In New York, childless adults up to 78% FPL were eligible for the Medicaid (Home Relief) waiver program and childless adults up to 100% FPL were eligible for the Family Health Plus waiver program (Heberlein et al., 2011).

¹¹ In Vermont, childless adults up to 150% FPL were eligible for Medicaid-equivalent coverage through the Vermont Health Access Plan waiver program (Heberlein et al., 2011).

¹² Although Wisconsin was not an ACA expansion state, the state received federal approval to offer Medicaid to childless adults below 100% FPL through the BadgerCare program without an enrollment cap (Gates & Rudowitz, 2014).

¹³ Pennsylvania, Indiana, Alaska, and Montana expanded Medicaid in 2015 and are therefore identified as “non-expansion” as our data only go through 2014.

Table 2. Descriptive Statistics of Low-Income, Non-Elderly, Childless Adults Sample

	<u>Treatment Group</u>		<u>Control Group</u>		Pre-expansion difference (5)
	Before expansion (1)	After expansion (2)	Before expansion (3)	After expansion (4)	
<i>Panel 1: Demographics</i>					
Age	41.32 (14.68)	41.07 (0.15)	42.26 (14.57)	41.86 (14.94)	-0.95**
Household Income	\$11,371 (\$2,910)	\$12,679 (\$4,209)	\$11,376 (\$3,277)	\$12,769 (\$4,013)	-4.75
Years Schooling	11.96 (2.70)	11.91 (2.94)	11.68 (2.83)	11.68 (2.97)	0.28***
Indicator: Female	0.49 (0.50)	0.47 (0.50)	0.51 (0.50)	0.52 (0.50)	-0.02
Indicator: Married	0.15 (0.36)	0.17 (0.38)	0.17 (0.38)	0.21 (0.41)	-0.02**
Indicator: Unemployed	0.24 (0.43)	0.19 (0.39)	0.23 (0.42)	0.18 (0.38)	0.01
Race Indicators					
White (non-Hispanic)	0.59	0.55	0.52	0.48	0.07***
Black	0.21	0.19	0.25	0.25	-0.03**
Native American	0.02	0.01	0.02	0.02	0.002
Asian	0.02	0.03	0.01	0.02	0.007**
Pacific Islander	0.01	0.001	0.01	0.002	0.001
Other	0.01	0.01	0.01	0.01	-0.001
Multiracial	0.02	0.02	0.02	0.02	-0.01*
Hispanic	0.13	0.19	0.16	0.20	-0.03***
<i>Panel 2: Insurance</i>					
Indicator: Have insurance	0.56 (0.50)	0.74 (0.44)	0.52 (0.50)	0.56 (0.50)	0.04**
<i>Panel 3: Access to care</i>					
Index: Good access to care indicator	0.82 (0.38)	0.87 (0.33)	0.80 (0.40)	0.82 (0.38)	0.02*
Indicator: Have personal doctor	0.65 (0.48)	0.68 (0.47)	0.60 (0.49)	0.61 (0.49)	0.05***
Indicator: Cost a barrier to care	0.38 (0.49)	0.32 (0.47)	0.42 (0.49)	0.39 (0.49)	-0.04***
<i>Panel 4: Preventive care</i>					
Index: Number of preventive services received	1.43 (1.02)	1.77 (1.07)	1.45 (1.03)	1.66 (1.07)	-0.02
Indicator: Routine checkup (in past 1 year)	0.59 (0.49)	0.65 (0.48)	0.59 (0.49)	0.61 (0.49)	-0.00
Indicator: Flu shot (in past 1 year)	0.26 (0.44)	0.30 (0.46)	0.26 (0.44)	0.28 (0.45)	0.00
Indicator: HIV test (ever)	0.43 (0.50)	0.43 (0.49)	0.45 (0.49)	0.46 (0.50)	-0.02

Indicator: Dentist visit (in past 1 year)	0.42 (0.49)	0.45 (0.50)	0.42 (0.49)	0.38 (0.49)	0.00
Index: Received any cancer screenings indicator (women)	0.55 (0.50)	0.63 (0.48)	0.58 (0.49)	0.59 (0.49)	-0.03
Indicator: Clinical breast exam (in past 1 year; women above 21)	0.41 (0.49)	0.47 (0.50)	0.44 (0.50)	0.43 (0.50)	-0.03
Indicator: Pap test (in past 1 year; women above 21)	0.36 (0.48)	0.39 (0.49)	0.40 (0.49)	0.37 (0.48)	-0.04
Indicator: Mammogram (in past 1 year; women above 50)	0.43 (0.50)	0.50 (0.50)	0.47 (0.50)	0.49 (0.50)	-0.04**
<hr/>					
<i>Panel 5: Health behaviors</i>					
Index: At least 1 unhealthy behavior indicator	0.77 (0.42)	0.76 (0.42)	0.78 (0.41)	0.78 (0.42)	-0.01
Indicator: Current smoker	0.37 (0.48)	0.34 (0.48)	0.37 (0.48)	0.35 (0.48)	-0.00
Indicator: Heavy drinking in past month	0.08 (0.27)	0.06 (0.2)	0.05 (0.22)	0.06 (0.23)	0.03***
Indicator: Binge drinking in past month	0.20 (0.40)	0.17 (0.38)	0.16 (0.37)	0.16 (0.36)	0.04***
Indicator: Exercise in past month	0.66 (0.47)	0.64 (0.48)	0.62 (0.49)	0.62 (0.49)	0.04***
BMI (x100)	2839.74 (770.15)	2847.73 (800.61)	2882.49 (794.97)	2891.81 (792.26)	-42.75**
Indicator: Obese	0.33 (0.47)	0.34 (0.47)	0.35 (0.48)	0.36 (0.48)	-0.02*
<hr/>					
<i>Panel 6: Self-assessed health</i>					
General health (range 1-5)	2.82 (1.23)	2.93 (1.20)	2.78 (1.25)	2.78 (1.25)	0.04
Index: Number of unhealthy days	14.44 (13.29)	13.52 (13.03)	14.69 (13.33)	14.04 (13.32)	-0.25
Number days mental health not good (in past month)	8.88 (11.51)	7.83 (10.89)	8.95 (11.53)	8.67 (11.49)	-0.07
Number days physical health not good (in past month)	8.76 (11.64)	7.78 (10.96)	9.14 (11.77)	8.49 (11.62)	-0.38
Number days poor health prevented work (in past month)	10.37 (11.90)	9.25 (11.48)	10.62 (12.05)	10.58 (12.13)	-0.25

Notes: Source: Author estimates based on BRFSS 2012-14. Standard deviations are in parentheses. Sample was restricted to include only non-elderly, <100% FPL, childless adults who are not pregnant and not veterans. N=10,555 for the treatment group and N=19,828 for the control group. However, because of missing data (respondents either refused to answer, responded “unsure,” or were not asked the question), the number of valid observations varies for each outcome. Data is adjusted by BRFSS sample weights. States that offered at least some categorical eligibility for childless adults before 2014 are excluded from this analysis (See Table 1 for states in

treatment, control, and excluded categories). *** Difference significant at 1% level, **Significant at 5% level, * Significant at 10% level. See Appendix A for variable definitions.

Table 3. Tests for Parallel Trends Pre-Expansion among Childless Adults

Outcome Variable	Interaction for time trend and an indicator variable for treatment group		
	Coefficient	State-clustered standard error	N
<i>Panel 1: Insurance</i>			
Indicator: Have insurance	-0.002	0.0040	20,022
<i>Panel 2: Access to care</i>			
Index: Good access to care indicator	0.003	0.0044	20,075
Indicator: Have personal doctor	0.002	0.0036	20,053
Indicator: Cost a barrier to care	-0.001	0.0041	20,052
<i>Panel 3: Preventive care</i>			
Index: Number of preventive services received	-0.020**	0.0098	20,130
Indicator: Routine checkup (in past 1 year)	-0.013*	0.0067	19,746
Indicator: Flu shot (in past 1 year)	-0.003	0.0032	19,065
Indicator: HIV test (ever)	-0.004	0.0048	18,399
Indicator: Dentist visit (in past 1 year)	-0.011	0.0138	9,766
Index: Received any cancer screenings indicator (women)	-0.035	0.0241	5,363
Indicator: Clinical breast exam (in past 1 year; women above 21)	-0.017	0.0182	5,372
Indicator: Pap test (in past 1 year; women above 21)	-0.003	0.0337	3,421
Indicator: Mammogram (in past 1 year; women above 50)	-0.011	0.0441	3,894
<i>Panel 4: Health behaviors</i>			
Index: At least 1 unhealthy behavior indicator	-0.006	0.0041	19,382
Indicator: Current smoker	-0.007	0.0072	19,732
Indicator: Heavy drinking in past month	-0.003	0.0027	19,310
Indicator: Binge drinking in past month	-0.006	0.0041	19,280
Indicator: Exercise in past month	0.009**	0.0039	19,450
BMI (x100)	4.32	7.247	19,316
Indicator: Obese	0.004	0.0034	19,316
<i>Panel 5: Self-assessed health</i>			
General health (range 1-5)	0.005	0.0069	20,006
Index: Number of unhealthy days	0.028	0.0906	20,130
Number days mental health not good (in past month)	-0.023	0.0944	19,552
Number days physical health not good (in past month)	-0.034	0.0774	19,481
Number days poor health prevented work (in past month)	0.060	0.151	14,798

Notes: Author estimates based on BRFSS 1st quarter 2012-4th quarter 2013. Sample was restricted to include only non-elderly, <100% FPL, childless adults who are not pregnant and not veterans. All regressions also control for gender, marital status, household size, race, unemployment status, age, education, state unemployment rate, whether the respondent was part of the cell-phone sample, state-fixed effects, and quarter/year-fixed effects. Data is adjusted by BRFSS sample weights. States that offered at least some categorical eligibility for childless adults before 2014 are excluded from this analysis (See Table

1 for states in treatment, control, and excluded categories). *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 4. DD Estimates for Impact of Medicaid Expansion on Insurance and Behaviors for Low-Income, Non-Elderly Childless Adults

	Pre-2014 mean, treatment (1)	Women and men, pooled (2)	Women only (3)	Men only (4)	Difference, women and men (5)
<i>Panel 1:</i>					
<i>Insurance</i>					
Indicator: Have insurance	0.56 (0.50)	0.155*** (0.0216) N=29,395	0.171*** (0.0295) N=18,121	0.142*** (0.0273) N=11,274	0.028
<i>Panel 2: Access to care</i>					
Index: Good access to care indicator	0.82 (0.38)	0.033* (0.0157) N=29,473	0.025 (0.0206) N=18,140	0.032 (0.0206) N=11,333	-0.007
Indicator: Have personal doctor	0.65 (0.48)	0.025 (0.0252) N=29,424	0.020 (0.0235) N=18,125	0.026 (0.0316) N=11,299	-0.006
Indicator: Cost a barrier to care	0.38 (0.49)	-0.027** (0.0113) N=29,436	0.001 (0.0143) N=18,113	-0.052*** (0.0182) N=11,323	0.053**
<i>Panel 3: Preventive care</i>					
Index: Number of preventive services received	1.43 (1.02)	0.155** (0.0627) N=29,557	0.168*** (0.0563) N=18,189	0.153 (0.108) N=11,368	0.015
Indicator: Routine checkup (in past 1 year)	0.59 (0.49)	0.059** (0.0278) N=28,993	0.054** (0.0257) N=17,854	0.063 (0.0480) N=11,139	-0.010
Indicator: Flu shot (in past 1 year)	0.26 (0.44)	0.016 (0.0244) N=28,131	0.025 (0.0240) N=17,377	0.010 (0.0401) N=10,754	0.015
Indicator: HIV test (ever)	0.43 (0.50)	-0.007 (0.0265) N=27,069	-0.019 (0.0325) N=16,710	0.007 (0.0375) N=10,359	-0.026
Indicator: Dentist visit (in past 1 year)	0.42 (0.49)	0.084*** (0.0151) N=19,079	0.110*** (0.0209) N=11,671	0.058*** (0.0210) N=7,408	0.052*
Index: Received any cancer screenings indicator (women)	0.55 (0.50)	0.067 (0.0448) N=10,232	0.067 (0.0448) N=10,232		
Indicator: Clinical breast exam (in past 1 year; women above 21)	0.41 (0.49)	0.058* (0.0337) N=10,254	0.058* (0.0337) N=10,254		
Indicator: Pap test (in past 1 year; women above 21)	0.36 (0.48)	0.090 (0.0629) N=6,623	0.090 (0.0629) N=7,152		
Indicator: Mammogram (in past 1 year; women above 50)	0.43 (0.50)	0.068* (0.0344) N=7,362	0.068* (0.0344) N=7,362		

Panel 4: Health behaviors

Index: At least 1 unhealthy behavior indicator	0.77 (0.42)	0.013 (0.0126) N=28,495	-0.009 (0.0152) N=17,508	0.031 (0.0231) N=10,987	-0.039
Indicator: Current smoker	0.37 (0.48)	0.020 (0.0166) N=28,884	0.014 (0.0216) N=17,807	0.027 (0.0244) N=11,077	-0.014
Indicator: Heavy drinking in past month	0.08 (0.27)	-0.025** (0.0099) N=28,228	-0.032* (0.0164) N=17,517	-0.017 (0.0132) N=10,711	-0.014
Indicator: Binge drinking in past month	0.20 (0.40)	-0.024 (0.0225) N=28,217	-0.031 (0.0246) N=17,516	-0.013 (0.0309) N=10,701	-0.018
Indicator: Exercise in past month	0.66 (0.47)	-0.026 (0.0240) N=28,859	-0.032 (0.0306) N=17,781	-0.023 (0.0392) N=11,078	-0.008
BMI (x100)	2839.74 (770.15)	0.143 (31.82) N=28,328	-23.60 (43.24) N=17,227	17.64 (35.35) N=11,101	-41.23
Indicator: Obese	0.33 (0.47)	0.003 (0.0218) N=28,328	0.004 (0.0293) N=17,227	-0.001 (0.0269) N=11,101	0.004

Panel 5: Self-assessed health

General health (range 1-5)	2.82 (1.23)	0.098* (0.0485) N=29,385	0.099** (0.0484) N=18,083	0.111* (0.0583) N=11,302	-0.012
Index: Number of unhealthy days	14.44 (13.29)	-0.155 (0.481) N=29,557	-0.032 (0.813) N=18,189	-0.423 (0.704) N=11,368	0.391
Number days mental health not good (in past month)	8.88 (11.51)	-0.530 (0.543) N=28,722	-0.618 (0.707) N=17,694	-0.660 (0.823) N=11,028	0.042
Number days physical health not good (in past month)	8.76 (11.64)	-0.456 (0.423) N=28,596	0.183 (0.636) N=17,608	-1.105** (0.536) N=10,988	1.288
Number days poor health prevented work (in past month)	10.37 (11.90)	-0.808* (0.402) N=21,597	-0.537 (0.606) N=13,947	-1.011 (0.775) N=7,650	0.474

Notes: Author estimates based on BRFSS 2012-14. Sample was restricted to include only non-elderly, <100% FPL, childless adults who are not pregnant and not veterans. The cancer screenings regressions were limited to women above age 21, and the mammogram regression was limited to women over age 50. State-clustered standard errors are in parentheses for regressions. Standard deviations are in parentheses for pre-treatment means. All regressions also control for gender, marital status, household size, race, unemployment status, age, education, state unemployment rate, whether the respondent was part of the cell-phone sample, state-fixed effects, and quarter/year-fixed effects. Data is adjusted by BRFSS sample weights. States that offered at least some categorical eligibility for childless adults before 2014 are excluded from this analysis. (See Table 1 for states in treatment, control, and excluded categories.) Column 1 displays variable's mean value for the treatment group in 2012-13, adjusted by BRFSS sample weight. Larger fonts indicate summary measures and smaller fonts indicate detailed outcomes. See Appendix A for variable definitions. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 5. Falsification Tests, DD Estimates

	<u>Over age 65</u> Pre-2014 mean, treatment	DD Estimates	<u>High-Income</u> Pre-2014 mean, treatment	DD Estimates
<i>Panel 1: Insurance</i>				
Indicator: Have insurance	0.98 (0.14)	-0.001 (0.0037) N=247,762	0.99 (0.09)	-0.003 (0.0038) N=15,272
<i>Panel 2: Access to care</i>				
Index: Good access to care indicator	0.99 (0.07)	0.001 (0.0011) N=248,223	0.99 (0.07)	0.004 (0.0027) N=15,282
Indicator: Have personal doctor	0.95 (0.21)	-0.003 (0.0031) N=247,611	0.95 (0.21)	-0.001 (0.0148) N=15,258
Indicator: Cost a barrier to care	0.05 (0.22)	-0.001 (0.0028) N=247,691	0.02 (0.15)	-0.003 (0.0070) N=15,266
<i>Panel 3: Preventive care</i>				
Index: Number of preventive services received	1.82 (0.87)	-0.003 (0.0175) N=248,406	1.93 (0.91)	-0.022 (0.0548) N=15,285
Indicator: Routine checkup (in past 1 year)	0.86 (0.34)	-0.007 (0.0069) N=244,303	0.86 (0.34)	-0.024 (0.0165) N=15,146
Indicator: Flu shot (in past 1 year)	0.59 (0.49)	0.0003 (0.0130) N=237,142	0.59 (0.49)	-0.005 (0.0391) N=14,841
Indicator: HIV test (ever)	0.10 (0.30)	0.001 (0.0043) N=225,818	0.13 (0.34)	0.018 (0.0175) N=14,259
Indicator: Dentist visit (in past 1 year)	0.66 (0.47)	-0.008 (0.0068) N=158,116	0.84 (0.37)	-0.028 (0.0214) N=9,451
Index: Received any cancer screenings indicator (women)	0.70 (0.46)	-0.005 (0.0094) N=123,278	0.77 (0.42)	-0.025 (0.0270) N=7,051
Indicator: Clinical breast exam (in past 1 year; women above 21)	0.53 (0.50)	0.017** (0.0075) N=123,924	0.65 (0.48)	-0.008 (0.0410) N=7,071
Indicator: Pap test (in past 1 year; women above 21)	0.25 (0.44)	0.004 (0.0121) N=62,545	0.32 (0.47)	0.067** (0.0319) N=3,984
Indicator: Mammogram (in past 1 year; women above 50)	0.60 (0.49)	-0.003 (0.0100) N=124,070	0.67 (0.47)	-0.019 (0.0338) N=7,080
<i>Panel 4: Health behaviors</i>				
Index: At least 1 unhealthy behavior indicator	0.58 (0.49)	0.012 (0.0077) N=234,666	0.49 (0.50)	0.059* (0.0291) N=14,642
Indicator: Current smoker	0.09 (0.29)	0.007* (0.0043) N=241,347	0.07 (0.25)	-0.005 (0.0174) N=15,019
Indicator: Heavy drinking in past month	0.04 (0.19)	0.0003 (0.0027) N=238,305	0.07 (0.26)	-0.017 (0.0155) N=14,854

Indicator: Binge drinking in past month	0.04 (0.19)	-0.001 (0.0024) N=238,535	0.06 (0.24)	-0.008 (0.0085) N=14,867
Indicator: Exercise in past month	0.66 (0.47)	0.001 (0.0099) N=242,990	0.78 (0.41)	-0.041 (0.0291) N=15,054
BMI (x100)	2747.24 (554.54)	12.70 (7.64) N=237,103	2696.74 (534.54)	44.21 (27.99) N=14,931
Indicator: Obese	0.27 (0.44)	0.010 (0.0065) N=237,103	0.23 (0.42)	0.055** (0.0220) N=14,931

Panel 5: Self-assessed health

General health (range 1-5)	3.20 (1.09)	-0.011 (0.0146) N=247,053	3.65 (1.00)	-0.069 (0.0572) N=15,235
Index: Number of unhealthy days	7.32 (11.21)	0.106 (0.157) N=248,406	5.19 (9.69)	-0.094 (0.494) N=15,285
Number days mental health not good (in past month)	2.42 (6.62)	0.021 (0.121) N=242,063	1.62 (5.19)	0.781** (0.344) N=15,044
Number days physical health not good (in past month)	5.19 (9.61)	0.043 (0.131) N=238,325	3.38 (7.92)	-0.150 (0.440) N=14,952
Number days poor health prevented work (in past month)	5.54 (0.75)	-0.087 (0.207) N=117,277	4.31 (8.57)	-1.081 (0.655) N=6,150

Notes: Author estimates based on BRFSS 2012-14. The cancer screenings regressions were limited to women above age 21, and the mammogram regression was limited to women over age 50. State-clustered standard errors are in parentheses for DD regressions. Standard deviations are in parentheses for pre-treatment means. All regressions also control for gender, marital status, household size, race, unemployment status, age, education, state unemployment rate, whether the respondent was part of the cell-phone sample, state-fixed effects, and quarter/year-fixed effects. Data is adjusted by BRFSS sample weights. States that offered at least some categorical eligibility for childless adults before 2014 are excluded from this analysis. (See Table 1 for states in treatment, control, and excluded categories.) Larger fonts indicate summary measures and smaller fonts indicate detailed outcomes. See Appendix A for variable definitions. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 6A. Sensitivity Analyses, DD Estimates

	Logit model (1)	Without BRFSS weights (2)	Linear state time trend (3)	Excluding 2014:Q1&Q2 (4)	States with lowest 2013 insurance rates (5)
<i>Panel 1: Insurance</i>					
Indicator: Have insurance	0.170*** (0.023) N=29,379	0.139*** (0.0192) N=29,395	0.125*** (0.0271) N=29,395	0.201*** (0.0261) N=24,279	0.171*** (0.0422) N=21,393
<i>Panel 2: Access to care</i>					
Index: Good access to care indicator	0.036** (0.0154) N=29,457	0.025*** (0.0086) N=29,473	-0.006 (0.0298) N=29,473	0.046 (0.0293) N=24,346	0.029 (0.0229) N=21,457
Indicator: Have personal doctor	0.028 (0.0259) N=29,408	0.021* (0.0122) N=29,424	-0.009 (0.0378) N=29,424	0.045 (0.0276) N=24,313	0.002 (0.0359) N=21,425
Indicator: Cost a barrier to care	-0.029*** (0.0114) N=29,430	-0.024** (0.0099) N=29,436	-0.002 (0.0283) N=29,436	-0.044 (0.0282) N=24,313	-0.031* (0.0167) N=21,429
<i>Panel 3: Preventive care</i>					
Index: Number of preventive services received		0.100*** (0.0360) N=29,557	0.246*** (0.0694) N=29,557	0.198** (0.0913) N=24,415	0.186* (0.107) N=21,526
Indicator: Routine checkup (in past 1 year)	0.061** (0.0287) N=28,984	0.042*** (0.0105) N=28,993	0.123** (0.0524) N=28,993	0.074* (0.0425) N=23,947	0.0903** (0.0433) N=21,115
Indicator: Flu shot (in past 1 year)	0.015 (0.0243) N=28,123	0.013 (0.0188) N=28,131	0.016 (0.0274) N=28,131	0.032 (0.0296) N=23,173	0.023 (0.0405) N=20,509
Indicator: HIV test (ever)	-0.007 (0.0266) N=27,062	0.004 (0.0151) N=27,069	0.029 (0.0349) N=27,069	-0.014 (0.0328) N=22,302	0.014 (0.0257) N=19,753
Indicator: Dentist visit (in past 1 year)	0.084*** (0.0148) N=19,075	0.037* (0.0213) N=19,079	0.122 (0.0791) N=19,079	0.092*** (0.0249) N=13,998	0.066*** (0.0209) N=13,924
Index: Received any cancer screenings indicator (women)	0.068 (0.0448) N=10,222	0.044 (0.0317) N=10,232	0.176 (0.138) N=10,232	0.068 (0.0647) N=7,605	0.021 (0.0804) N=7,432
Indicator: Clinical breast exam (in past 1 year; women above 21)	0.058* (0.0334) N=10,246	0.047* (0.0263) N=10,254	0.169 (0.138) N=10,254	0.048 (0.0436) N=7,624	0.033 (0.0467) N=7,444
Indicator: Pap test (in past 1 year; women above 21)	0.089 (0.0622) N=6,621	0.005 (0.0352) N=6,623	0.142 (0.165) N=6,623	0.070 (0.0827) N=4,882	0.059 (0.0978) N=4,748
Indicator: Mammogram (in past 1 year; women above 50)	0.069** (0.0343) N=7,359	0.046* (0.0247) N=7,362	0.103 (0.264) N=7,362	0.046 (0.0302) N=5,506	0.027 (0.0544) N=5,326
<i>Panel 4: Health behaviors</i>					
Index: At least 1 unhealthy behavior indicator	0.013 (0.0125) N=28,466	-0.002 (0.0012) N=28,495	0.053 (0.0341) N=28,495	-0.012 (0.0206) N=23,526	0.033** (0.0122) N=20,759
Indicator: Current smoker	0.019 (0.0164) N=28,880	-0.006 (0.0096) N=28,884	0.043 (0.0429) N=28,884	0.010 (0.0234) N=23,878	0.052** (0.0206) N=21,040
Indicator: Heavy drinking in past month	-0.022** (0.0090)	-0.007 (0.0055)	-0.008 (0.0248)	-0.026* (0.0109)	-0.032** (0.0146)

	N=28,217	N=28,228	N=28,228	N=23,340	N=20,543
Indicator: Binge drinking in past month	-0.023 (0.0220)	0.004 (0.0106)	0.012 (0.0373)	-0.025 (0.0213)	-0.029 (0.0394)
	N=28,212	N=28,217	N=28,217	N=23,317	N=20,533
Indicator: Exercise in past month	-0.025 (0.0239)	-0.002 (0.0139)	-0.070** (0.0329)	-0.035 (0.0267)	-0.028 (0.0246)
	N=28,853	N=28,859	N=28,859	N=23,723	N=21,030
BMI (x100)		8.38 (22.51)	-14.27 (60.25)	-36.27 (35.48)	-27.42 (42.92)
		N=28,328	N=28,328	N=23,405	N=20,634
Indicator: Obese	0.003 (0.0218)	0.003 (0.0139)	-0.010 (0.0372)	-0.015 (0.0305)	0.008 (0.0329)
	N=28,313	N=28,328	N=28,328	N=23,405	N=20,634

Panel 5: Self-assessed health

General health (range 1-5)		0.073** (0.0302)	0.112* (0.0681)	0.029 (0.0479)	0.076 (0.0758)
		N=29,385	N=29,385	N=24,267	N=21,385
Index: Number of unhealthy days		-0.690 (0.425)	-0.724 (0.646)	0.184 (0.712)	0.407 (0.668)
		N=29,557	N=29,557	N=24,415	N=21,526
Number days mental health not good (in past month)		-0.726** (0.290)	-0.614 (0.637)	-0.445 (0.701)	-0.217 (0.571)
		N=28,722	N=28,722	N=23,708	N=20,905
Number days physical health not good (in past month)		-0.519 (0.456)	-0.544 (0.601)	-0.229 (0.468)	-0.263 (0.396)
		N=28,596	N=28,596	N=23,628	N=20,803
Number days poor health prevented work (in past month)		-0.628* (0.327)	-1.688** (0.831)	-0.294 (0.431)	-1.169** (0.556)
		N=21,597	N=21,597	N=17,857	N=15,669

Notes: Author estimates based on BRFSS 2012-14. Sample was restricted to include only non-elderly, <100% FPL, childless adults who are not pregnant and not veterans. State-clustered standard errors are in parentheses. All regressions also control for gender, marital status, household size, race, unemployment status, age, education, state unemployment rate, whether the respondent was part of the cell-phone sample, state-fixed effects, and quarter/year-fixed effects. Data is adjusted by BRFSS sample weights. States that offered at least some categorical eligibility for childless adults before 2014 are excluded from this analysis (See Table 1 for states in treatment, control, and excluded categories). Column 1 displays marginal effects. In Column 5, we use only the four expansion states with the lowest pre-2014 insurance rates (IL, AR, NJ, and NV) as our treatment group and all 22 non-expansion states as our control group. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Table 6B. Sensitivity Analyses, DD Estimates

	Parents and childless adults (1)	Broader expansion definition (2)	Low education sample (3)
<i>Panel 1: Insurance</i>			
Indicator: Have insurance	0.098*** (0.0183) N=47,863	0.091*** (0.0203) N=40,387	0.045*** (0.0143) N=25,866
<i>Panel 2: Access to care</i>			
Index: Good access to care indicator	0.021 (0.0171) N=47,996	0.021 (0.0134) N=40,496	0.007 (0.0166) N=25,953
Indicator: Have personal doctor	0.012 (0.0231) N=47,892	0.020 (0.0203) N=40,419	0.040*** (0.0111) N=25,866
Indicator: Cost a barrier to care	-0.022 (0.0143) N=47,951	-0.047*** (0.0141) N=40,449	0.018 (0.0241) N=25,919
<i>Panel 3: Preventive care</i>			
Index: Number of preventive services received	0.107** (0.0470) N=48,123	0.099*** (0.0351) N=40,611	0.050 (0.0633) N=26,042
Indicator: Routine checkup (in past 1 year)	0.017 (0.0181) N=47,211	0.030** (0.0156) N=39,897	0.020 (0.0316) N=25,478
Indicator: Flu shot (in past 1 year)	0.049** (0.0197) N=45,531	-0.003 (0.0170) N=38,336	-0.004 (0.0288) N=24,326
Indicator: HIV test (ever)	0.008 (0.0194) N=43,811	0.012 (0.0215) N=36,871	0.007 (0.0238) N=23,351
Indicator: Dentist visit (in past 1 year)	0.015 (0.0161) N=31,377	0.063*** (0.0154) N=26,645	-0.007 (0.0280) N=16,523
Index: Received any cancer screenings indicator (women)	-0.008 (0.0342) N=17,186	0.072* (0.0395) N=13,715	0.006 (0.0280) N=8,260
Indicator: Clinical breast exam (in past 1 year; women above 21)	-0.018 (0.0333) N=17,223	0.077** (0.0307) N=13,744	0.011 (0.0371) N=8,276
Indicator: Pap test (in past 1 year; women above 21)	0.010 (0.0360) N=12,320	0.067 (0.0642) N=9,153	-0.004 (0.0377) N=5,026
Indicator: Mammogram (in past 1 year; women above 50)	0.011 (0.0421) N=9,005	0.053* (0.0269) N=9,805	0.014 (0.0364) N=6,378
<i>Panel 4: Health behaviors</i>			
Index: At least 1 unhealthy behavior indicator	0.020 (0.0138) N=45,836	0.007 (0.0111) N=38,996	-0.015 (0.0161) N=24,777
Indicator: Current smoker	0.019 (0.0150) N=46,928	-0.007 (0.0136) N=39,612	-0.009 (0.0168) N=25,176
Indicator: Heavy drinking in past month	-0.007 (0.0062) N=45,814	-0.007 (0.0094) N=38,609	-0.026*** (0.0076) N=24,347
Indicator: Binge drinking in past month	-0.002 (0.0173) N=45,836	0.009 (0.0189) N=38,585	-0.019 (0.0168) N=24,344

Indicator: Exercise in past month	-0.020 (0.0172) N=46,843	0.004 (0.0197) N=39,513	-0.013 (0.0318) N=25,215
BMI (x100)	6.27 (27.53) N=45,229	-0.11 (28.20) N=38,913	33.60 (33.21) N=24,488
Indicator: Obese	0.006 (0.0137) N=45,229	0.005 (0.0174) N=38,913	-0.001 (0.0222) N=24,488
<hr/>			
<i>Panel 5: Self-assessed health</i>			
General health (range 1-5)	0.070** (0.0319) N=47,853	0.080** (0.0364) N=40,390	0.062 (0.0528) N=25,839
Index: Number of unhealthy days	0.454 (0.315) N=48,123	-0.587 (0.492) N=40,611	-0.500 (0.580) N=26,042
Number days mental health not good (in past month)	0.053 (0.378) N=46,896	-0.510 (0.428) N=39,541	-0.632 (0.413) N=25,090
Number days physical health not good (in past month)	0.242 (0.267) N=46,687	-0.338 (0.365) N=39,384	-0.537 (0.358) N=24,880
Number days poor health prevented work (in past month)	0.068 (0.331) N=34,320	-1.058** (0.408) N=29,603	-0.874 (0.677) N=16,901

Notes: Author estimates based on BRFSS 2012-14. Sample was restricted to include only non-elderly, <100% FPL, childless adults who are not pregnant and not veterans. State-clustered standard errors are in parentheses. All regressions also control for gender, marital status, household size, race, unemployment status, age, education, state unemployment rate, whether the respondent was part of the cell-phone sample, state-fixed effects, and quarter/year-fixed effects. Data is adjusted by BRFSS sample weights. The regression results presented in column 2 include all 50 states and DC. For columns 1 and 3, states that offered at least some categorical eligibility for childless adults before 2014 are excluded from the analysis (See Table 1 for states in treatment, control, and excluded categories). *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Appendix A: Variable Definitions

Below, we describe in detail each outcome we analyze, which fall into the categories of: insurance coverage, access to care, preventive care, health behaviors, and self-assessed health. For categories with multiple measures, we construct an overall index, but also examine the individual components as outcomes as well. The text of the questions is from the BRFSS questionnaires.

- *Indicator: Have Insurance:* Individuals were asked, “Do you have any kind of healthcare coverage, including health insurance, prepaid plans such as HMOs, or government plans such as Medicare or Indian Health Service?” Those who responded “Yes” were coded as “1,” those who responded “No” were coded as “0,” and those who responded “Don’t know/not sure” or “Refused” were coded as missing.
- *Index: Good access to care indicator:* We constructed this variable as a binary variable equal to 1 if the individual either responded “no” when asked if cost was a barrier to care *or* “yes” when asked if they had a primary care physician. The outcome was coded as 0 if the individual responded “yes” when asked if cost was a barrier to care *and* “no” when asked if they had a primary care physician.
 - *Indicator: Have personal doctor:* Individuals were asked, “Do you have one person you think of as your personal doctor or healthcare provider?” We coded the variable as 1 if the response was either “Yes, only one” or “Yes, more than one,” and coded it as 0 if the response was “No.” Those who responded “Don’t know/not sure” or “Refused” were coded as missing.
 - *Indicator: Cost a barrier to care:* Individuals were asked, “Was there a time in the past 12 months when you needed to see a doctor but could not because of cost?”

Those who responded “Yes” were coded as “1,” those who responded “No” were coded as “0,” and those who responded “Don’t know/not sure” or “Refused” were coded as missing.

- *Index: Number of preventive services received:* We constructed this index as the sum of the four components below. The index can theoretically range from 0 (for someone who received none of the four services below) to 4 (for someone who received all of the services below).
 - *Indicator: Routine checkup:* Individuals were asked, “About how long has it been since you last visited a doctor for a routine checkup? (A routine checkup is a general physical exam, not an exam for a specific injury, illness, or condition.)” Those who responded “Within past year” were coded as 1. Those who responded “Within past 2 years ([more than] 1 year but less than 2 years ago),” “Within past 5 years ([more than] 2 years but less than 5 years ago),” “5 or more years ago,” or “Never” were coded as 0. Those who responded “Don’t know/not sure” or “Refused” were coded as missing.
 - *Indicator: Flu shot:* Individuals were asked, “During the past 12 months, have you had either a flu shot or a flu vaccine that was sprayed in your nose?” Those who responded “Yes” were coded as “1,” those who responded “No” were coded as “0,” and those who responded “Don’t know/not sure” or “Refused” were coded as missing.
 - *Indicator: HIV test:* Individuals were asked, “Have you ever been tested for HIV? Do not count tests you may have had as part of a blood donation. Include testing fluid from your mouth.” Those who responded “Yes” were coded as “1,” those

who responded “No” were coded as “0,” and those who responded “Don’t know/not sure” or “Refused” were coded as missing.

- *Indicator: Dentist visit:* Individuals were asked, “How long has it been since you last visited a dentist or a dental clinic for any reason? Include visits to dental specialists, such as orthodontists.” Those who responded “Within past year” were coded as 1. Those who responded “Within past 2 years ([more than] 1 year but less than 2 years ago),” “Within past 5 years ([more than] 2 years but less than 5 years ago),” “5 or more years ago,” or “Never” were coded as 0. Those who responded “Don’t know/not sure” or “Refused” were coded as missing.
- *Index: Received any cancer screenings indicator:* We constructed this index only for women above 21 using the three components below. The variable was coded as 1 if the individual responded “yes” to having received *any* of the cancer screenings below in the past year and as 0 if the individual responded “no” for *all* of the cancer screenings below in the past year. It was coded as missing for individuals who had missing data for all three screenings.
 - *Indicator: Clinical breast exam:* Women were asked the questions, “A clinical breast exam is when a doctor, nurse, or other health professional feels the breast for lumps. Have you had a clinical breast exam?” and “How long has it been since your last breast exam?” We coded our outcome variable as 1 if the individual responded “yes” to the first question and “within past year” to the second question. We coded our outcome variable as 0 if the individual responded “no” or “don’t know/not sure” to the first question *or* responded “yes” to the first question and “within past 2 years ([more than] 1 year but less than 2 years ago),” “within

past 3 years ([more than] 2 years but less than 3 years ago),” “within past 5 years ([more than] 3 years but less than 5 years ago),” “5 or more years ago,” or “Don’t know/not sure” to the second question. We coded our outcome variable as missing if the response to either question was “Refused” or if the individual was not a woman above 21.

- *Indicator: Pap test:* Women were asked the questions, “A Pap test is a test for cancer of the cervix. Have you ever had a Pap test?” and “How long has it been since you had your last Pap test?” We coded our outcome variable as 1 if the individual responded “yes” to the first question and “within past year” to the second question. We coded our outcome variable as 0 if the individual responded “no” to the first question *or* responded “yes” to the first question and “within past 2 years ([more than] 1 year but less than 2 years ago),” “within past 3 years ([more than] 2 years but less than 3 years ago),” “within past 5 years ([more than] 3 years but less than 5 years ago),” “5 or more years ago,” or “Don’t know/not sure” to the second question. We coded our outcome variable as missing if the response to either question was “Refused” or if the individual was not a woman above 21.
- *Indicator: Mammogram:* Women were asked the questions, “A mammogram is an x-ray of each breast to look for breast cancer. Have you ever had a mammogram?” and “How long has it been since you had your last mammogram?” We coded our outcome variable as 1 if the individual responded “yes” to the first question and “within past year” to the second question. We coded our outcome variable as 0 if the individual responded “no” to the first

question *or* responded “yes” to the first question and “within past 2 years ([more than] 1 year but less than 2 years ago),” “within past 3 years ([more than] 2 years but less than 3 years ago),” “within past 5 years ([more than] 3 years but less than 5 years ago),” “5 or more years ago,” “Don’t know/not sure,” or “Refused” to the second question. We coded our outcome variable as missing if the response to the first question was “Refused” or “Don’t know/not sure,” or if the individual was not a woman above 50.

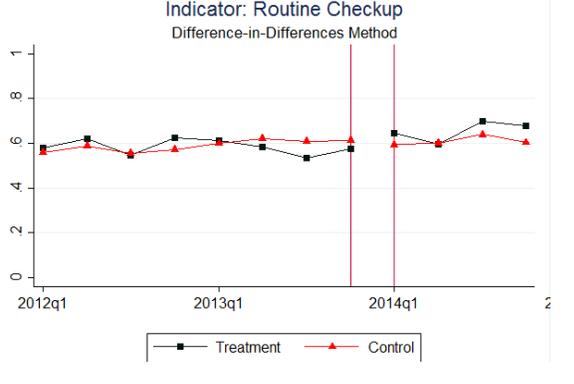
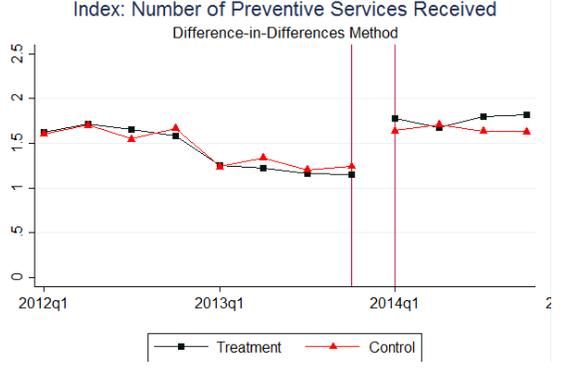
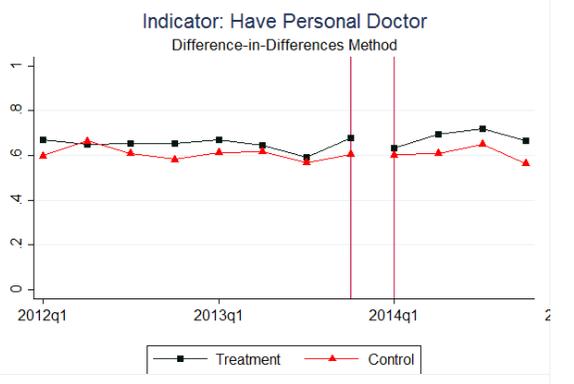
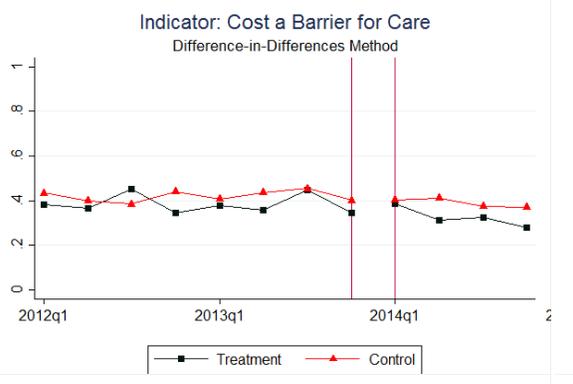
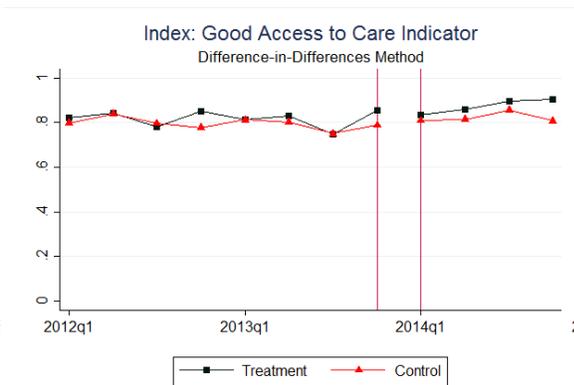
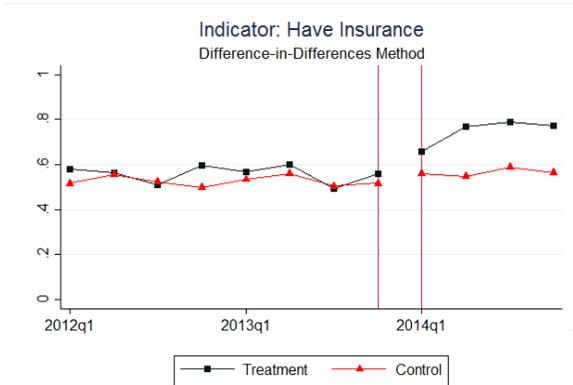
- *Index: At least one unhealthy behavior indicator:* We constructed this index using the components below. The variable was coded as 1 if the individual responded “yes” to being a current smoker, engaging in heavy drinking, or engaging in binge drinking, or “no” to having exercised in the past month, or if their reported height/weight qualifies as overweight/obese. The variable was coded as 0 if the individual is not obese *and* responded “no” to being a current smoker, engaging in heavy drinking, *and* engaging in binge drinking, *and* “yes” to having exercised in the past month. It was coded as missing for individuals who had missing data for all three variables.
 - *Indicator: Current smoker:* We constructed this using the BRFSS-calculated variable “Adults who are current smokers.” Those who currently smoke either every day or some days were coded as 1, and those who formerly smoked or never smoked were coded as 0. Those who responded “don’t know/not sure” or “refused” were coded as missing.
 - *Indicator: Heavy drinking:* We constructed this using the BRFSS-calculated variable “Heavy drinkers (adult men having more than two drinks per day and adult women having more than one drink per day)” during the past 30 days. Those

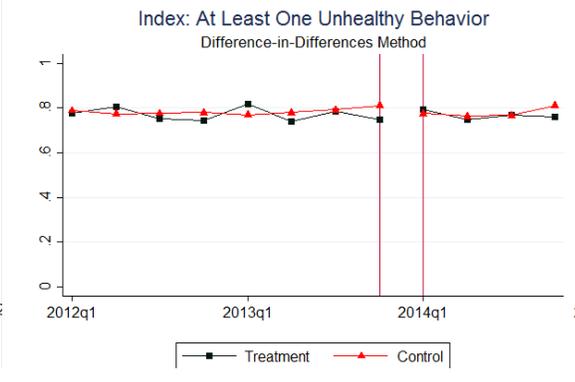
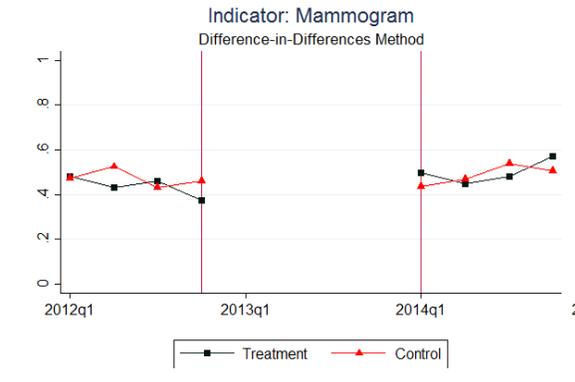
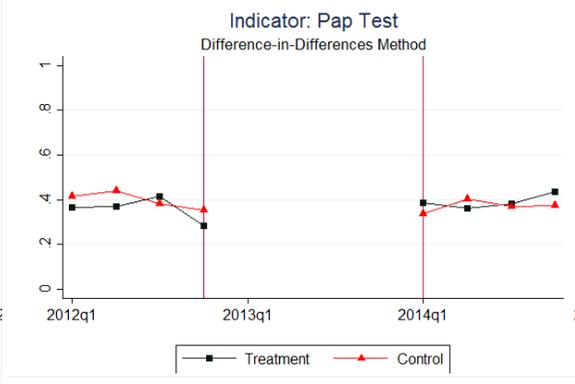
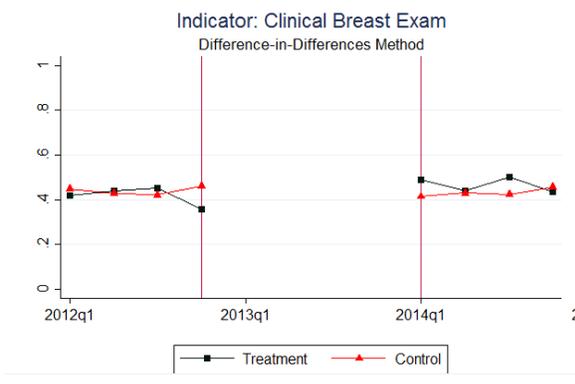
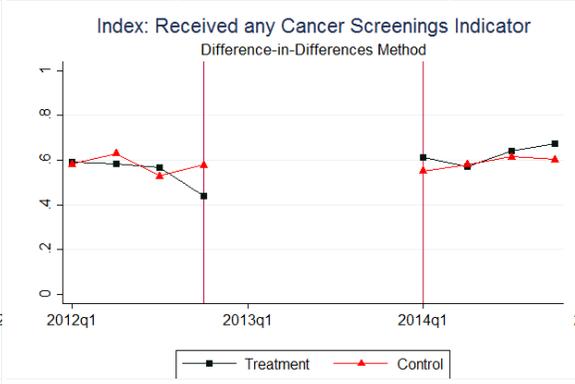
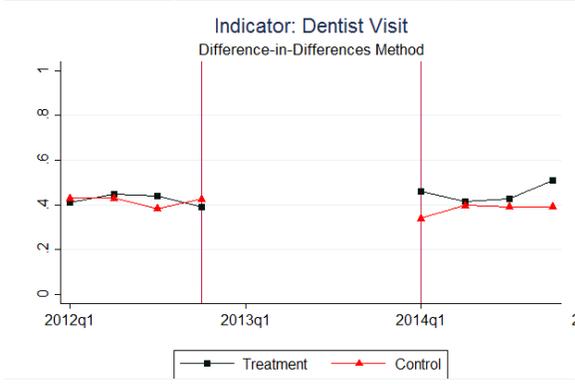
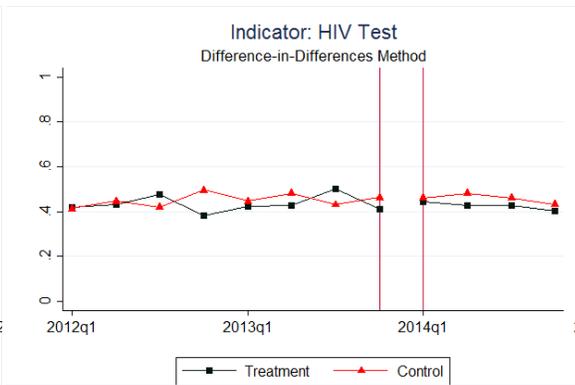
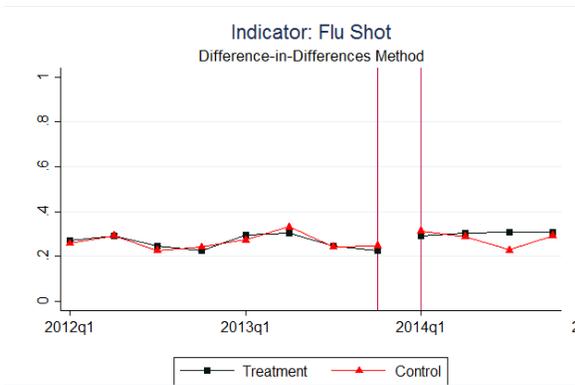
who engaged in heavy drinking were coded as 1, and those who did not were coded as 0. Those who responded “don’t know/not sure” or “refused” were coded as missing.

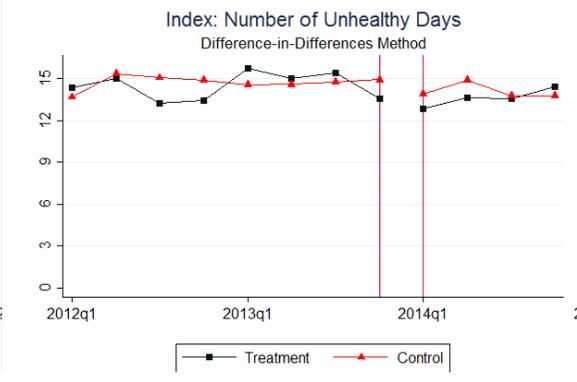
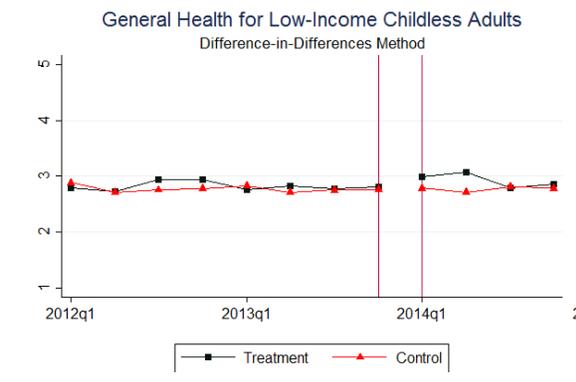
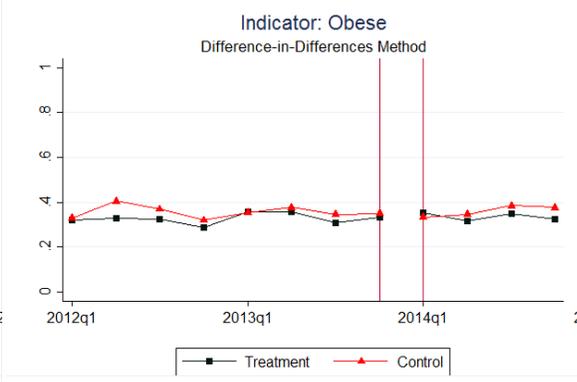
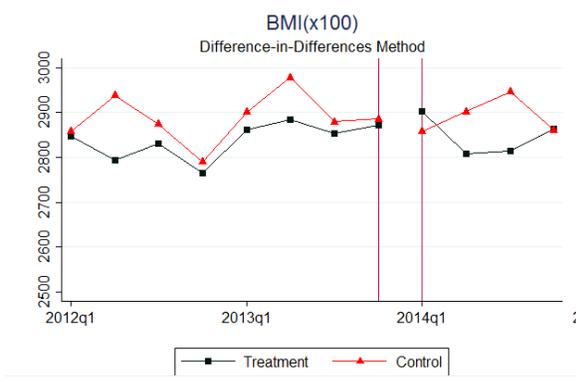
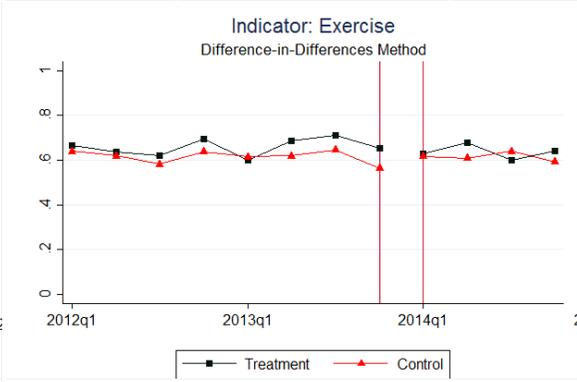
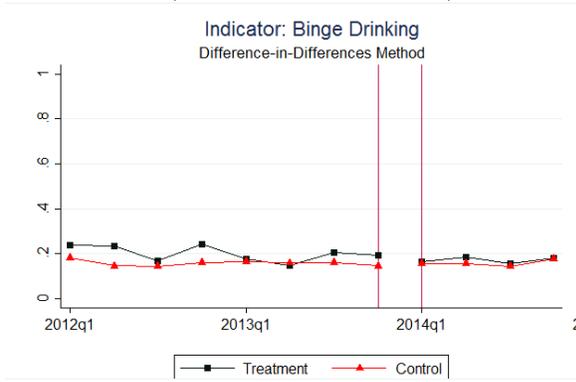
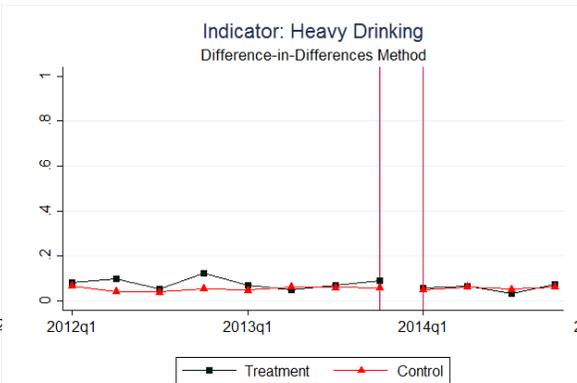
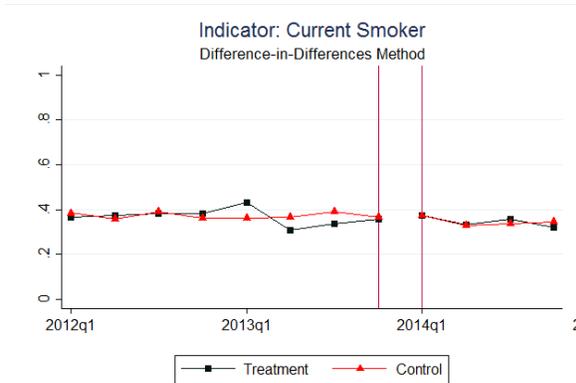
- *Indicator: Binge drinking:* We constructed this using the BRFSS calculated variable “Binge drinkers (males having five or more drinks on one occasion, females having four or more drinks on one occasion)” during the past 30 days. Those who engaged in binge drinking were coded as 1, and those who did not were coded as 0. Those who responded “don’t know/not sure” or “refused” were coded as missing.
- *Indicator: Exercise in past month:* Individuals were asked, “During the past month, other than your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise?” Those who responded “Yes” were coded as “1,” those who responded “No” were coded as “0,” and those who responded “Don’t know/not sure” or “Refused” were coded as missing.
- *BMI (x100):* This was a BRFSS-calculated variable using individuals’ reported height and weight. BRFSS divided weight by the square of height, and so the value has two implied decimal places. Those who reported height or weight as “Don’t know/not sure” or “Refused” were coded as missing.
- *Indicator: Obese:* We used the BRFSS-calculated BMI to construct this variable. Those whose BMI(x100) was calculated as greater than or equal to 3,000 but less than 9,999 were coded as 1. Those whose BMI(x100) was calculated as less than 2,500 were coded as 0. Those whose BMI was missing were coded as missing.

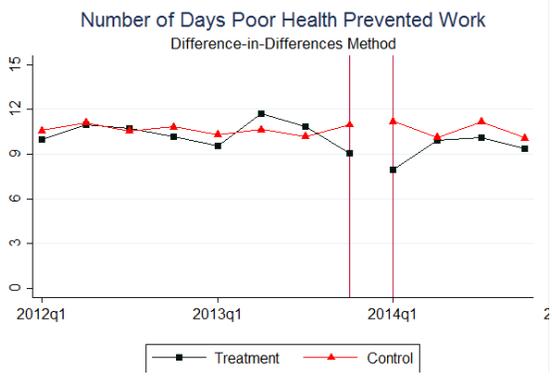
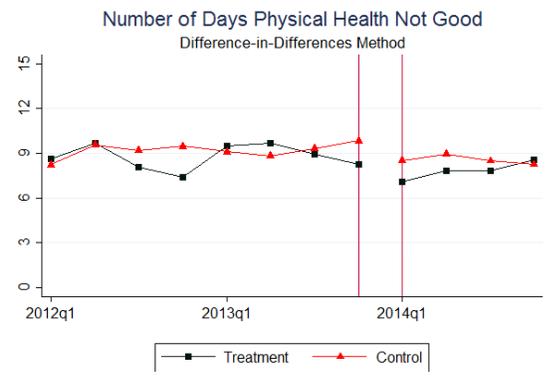
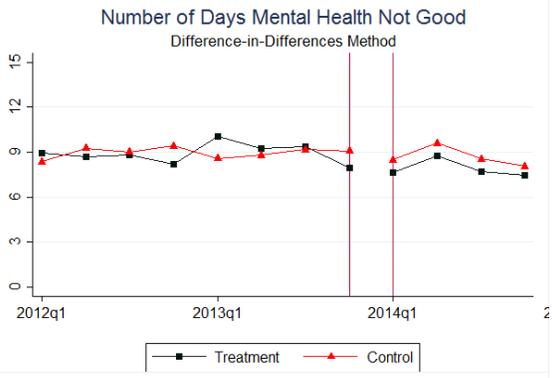
- *General Health*: Individuals were asked, “Would you say that in general your health is excellent, very good, good, fair, or poor?” We coded “Excellent” as 5, “Very good” as 4, “Good” as 3, “Fair” as 2, and “Poor” as 1. Those who responded “Don’t know/not sure” or “Refused” were coded as missing.
- *Index: Number of unhealthy days*: We constructed this index by taking the sum of the three components below and setting the max to 30.
 - *Number of mentally unhealthy days*: Individuals were asked, “Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?” This variable can theoretically range from 0 to 30. Those who responded “Don’t know/not sure” or “Refused” were coded as missing.
 - *Number of physically unhealthy days*: Individuals were asked, “Now thinking about your physical health, which includes physical illness and injury, for how many days during the past 30 days was your mental health not good?” This variable can theoretically range from 0 to 30. Those who responded “Don’t know/not sure” or “Refused” were coded as missing.
 - *Number of days poor health prevented work*: Individuals were asked, “During the past 30 days, for about how many days did poor physical or mental health keep you from doing your usual activities, such as self-care, work, or recreation?” This variable can theoretically range from 0 to 30. Those who responded “Don’t know/not sure” or “Refused” were coded as missing.

Appendix B: Trends in Outcomes, Treatment vs. Control States









Notes: Source is BRFSS 2012-2014. Sample was restricted to include only non-elderly, <100% FPL, childless adults who are not pregnant and not veterans. Data are adjusted by BRFSS sample weight. States that offered at least some categorical eligibility for childless adults before 2014 are excluded from this analysis (See Table 1 for states in treatment, control, and excluded categories). The vertical lines indicate Q4 of 2013 and Q1 of 2014; thus, Medicaid expansions took place in between the two vertical lines.

Data on dentist visits, cancer screenings index, clinical breast exams, Pap tests, and mammograms was not available for most states in BRFSS 2013, and so we drop the year 2013 only for these outcomes. Consequently, the number of preventive services received index (which sums dentist visits, flu shots, HIV tests, and routine checkups) drops for both the treatment and control group in 2013 because data for one component of the index (dentist visits) is not available in 2013.

Appendix C: Implied Elasticities of Health Behaviors with Respect to Insurance

We estimate that the Medicaid expansion resulted in a 15.5-percentage-point increase in the probability of having insurance coverage for low-income childless adults. The pre-2014 insurance rate for this population in treatment states was 56%, so our estimate implies that after controlling for other factors, the Medicaid expansion caused the insurance rate to rise from 56% to 72%. This represents a 27% rise in the insurance rate.

By combining the results for insurance with those for other outcomes, we are able to calculate elasticities of health behaviors with respect to insurance, assuming that insurance coverage is the sole pathway through which reform changes these outcomes.¹¹ To account for the fact that the sample size may be different for each outcome (due to missing data for certain individuals or certain years), we recalculate the DD estimate on insurance for each outcome, using only those individuals for whom the outcome variable is not missing. We use this revised estimate to calculate an elasticity for each outcome. For example, the Medicaid expansion caused a 15.7-percentage-point increase in the probability of having insurance as well as a 5.9-percentage-point increase in the probability of receiving a routine checkup in the past one year. This implies that 38% ($5.9/15.7=0.38$) of the newly insured received routine checkups in the past year. Table A1 presents elasticities with respect to insurance for all the statistically significant binary outcomes. In general, these outcomes are relatively inelastic with respect to health insurance; the most responsive outcome is dental visits, which has an elasticity with

¹¹ This would not be the case, for example, if the option to acquire insurance coverage in the future causes ex-ante moral hazard—that is, if uninsured individuals, knowing that they can enroll in Medicaid should they fall ill, engage in more risky behaviors. In this case, even individuals who are uninsured changed their health behaviors in response to the expansion. We set aside that possibility in these calculations, but note that it would make our elasticities smaller.

respect to health insurance of 0.54. The least responsive of these outcomes is heavy drinking, which has an elasticity with respect to health insurance of -0.15.

Table A1: Implied Elasticities of Health Outcomes with Respect to Insurance

Outcome Variable	Pre-2014 mean, treatment states (1)	DD estimate on outcome (2)	DD estimate on insurance (3)	Implied elasticity (4)	Implied post-2014 mean, treatment states (5)
<i>Panel 1: Access to care</i>					
Index: Good access to care indicator	0.82 (0.38)	0.033* (0.0157)	0.155*** (0.0215)	0.21	0.85
Indicator: Cost a barrier to care	0.38 (0.49)	-0.027** (0.0113)	0.154*** (0.0216)	-0.17	0.35
<i>Panel 2: Preventive care</i>					
Indicator: Routine checkup (in past 1 year)	0.59 (0.49)	0.059* (0.0278)	0.157*** (0.0218)	0.38	0.65
Indicator: Dentist visit (in past 1 year)	0.42 (0.49)	0.084*** (0.0151)	0.157*** (0.0219)	0.54	0.50
Indicator: Clinical breast exam (in past 1 year; women above 21)	0.41 (0.49)	0.058* (0.0337)	0.143*** (0.0362)	0.41	0.47
Indicator: Mammogram (in past 1 year; women above 50)	0.43 (0.50)	0.068* (0.0344)	0.183*** (0.0346)	0.37	0.50
<i>Panel 3: Health behaviors</i>					
Indicator: Heavy drinking in past month	0.08 (0.27)	-0.025** (0.0099)	0.162*** (0.0264)	-0.15	0.06

Notes: Author estimates based on BRFSS 2012-14. Results are from baseline regression displayed in Table 4, Column 2. Column 4 is the DD estimate on outcome divided by DD estimate on insurance. Column 5 is the pre-2014 mean plus the DD estimate on outcome. We display only binary outcomes that had statistically significant results. *** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.