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# Access to Health Care and Mental Health –

# Evidence from the ACA Preexisting Conditions Provision

Running Title: Access to Health Care and Mental Health

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## Abstract

This study evaluates the impact of the Affordable Care Act preexisting conditions provision on mental health. The 2014 policy ensured individuals with preexisting health conditions the right to obtain insurance coverage. Using longitudinal data from the Panel Study of Income Dynamics between 2007 and 2017 and estimating difference-in-differences models, our study provides evidence that the policy reduced severe mental distress by 1.44 percentage points (baseline mean: 8.09 percent) among individuals with preexisting physical health conditions. Exploiting pre-ACA, state-level variation in policies providing insurance coverage options to people with preexisting conditions, we find that this improvement in mental well-being is highly associated with the presence of high-risk pools before 2014, which provided individuals with prior health conditions access to coverage. Specifically, we show that our main results are driven by individuals with preexisting health conditions living in the 16 states that did not have high-risk pools. Furthermore, gender-specific analysis shows that the reduction in mental distress is primarily observable among women. When examining potential mechanisms, our analysis provides evidence that increases in insurance coverage, reductions in health care expenditures, and improvements in physical health can explain the positive effects of the provision on mental well-being.

**Keywords**: Affordable Care Act, Mental Health, Health Insurance, Financial Strain

**JEL Classifications**: I13, I18, J18

**Data Availability Statement**: The data that support the findings of this study are available from the corresponding author upon reasonable request.

**Conflicts of interest**: The authors have no conflicts of interest to disclose.

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## 1. INTRODUCTION

According to data from the Substance Abuse and Mental Health Services Administration (2019), 19.1 percent of American adults have any mental illness, with 4.6 percent suffering from severe mental illness. Moreover, only 43.3 percent of affected adults receive treatment, and 13.4 percent are uninsured, which exacerbates issues of mental health. With the recent prescription drug crisis and decline in labor force participation among prime-aged workers, issues related to mental health have become increasingly important in the United States (Krueger, 2016). Recent health care reform through The Patient Protection and Affordable Care Act (ACA) placed emphasis on mental health by defining it as one of the "ten essential benefits" of a health care plan.[1] Along with this, the ACA included protections for individuals with underlying health conditions through the preexisting conditions provision, which prevents insurers from denying coverage or charging unreasonable premiums. Given recent attitudes toward addressing mental health and access to health care in the U.S., it is plausible that the preexisting conditions provision improved mental health outcomes among this group.

Prior to the implementation of the preexisting conditions provision in 2014, individuals with health conditions were charged higher insurance premiums or denied coverage altogether. High-risk pools, which were in place in 35 states prior to the ACA, provide access to insurance coverage to individuals with prior health conditions. Estimates by Claxton et al. (2019) suggest that 27 percent (53.8 million) of nonelderly adults in the U.S. have a declinable health condition. Furthermore, Amadeo (2019) reports that among individuals with such conditions, 47 percent were denied private coverage prior to the ACA. The inability to obtain coverage could lead to increased mental illness or mental distress as

[1] The 10 essential health benefits of a marketplace insurance plan can be found at: https://www.healthcare.gov/coverage/what-marketplace-plans-cover/



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well as financial strain due to a lack of access to preventative care and high costs of emergency room treatment. Due to difficulty in obtaining insurance coverage prior to the ACA, individuals with preexisting health conditions potentially experienced lower levels of financial and subjective wellbeing. These effects are likely stronger in the 16 states that did not have high-risk pools in place prior to 2014.

In this study, we examine the effects of the ACA preexisting conditions provision on the self-perceived mental distress of individuals with prior physical health conditions.[2] While there is an abundance of work studying other elements of the ACA such as dependent coverage and Medicaid expansion, there is limited work studying effects of the preexisting conditions provision.[3] Our study adds to a sparse literature studying individuals with chronic conditions, and we are the first study to assess the impact of the ACA preexisting conditions provision on mental health. Using longitudinal data from the Panel Study of Income Dynamics (PSID) between 2007 and 2017 and estimating difference-in-differences models, we evaluate the effects of the 2014 federal policy change on mental distress. Exploiting state-level variation in the presence of high-risk pools prior to the policy, we separately evaluate the effects on mental distress for two groups of states: those with and without pre-ACA high-risk pools. Additionally, given that rates of mental illness differ substantially among males and females (34.9 vs 48.6 percent; National Alliance on Mental Illness, 2019), we also test for heterogeneous effects across gender.

Overall, we find that, compared to individuals without health conditions, the ACA preexisting conditions provision reduced the likelihood of severe mental distress among

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[2] While we provide statistics for mental illness in the opening paragraph, the main outcome of interest that we evaluate in our study is the prevalence of mental distress. As shown by Forman-Hoffman et al. (2014), the measure of mental distress used in our study is highly correlated with mental illness and is a strong indicator of diagnosable mental illness with considerable disability. Thus, we believe any potential findings on mental distress would provide suggestive evidence that the policy also affected mental illness.
[3] Medicaid is a U.S. Social Insurance program providing insurance coverage to the nation's most vulnerable populations, those with low-income or disabilities.



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individuals with prior physical health issues by 1.44 percentage points from a baseline mean of 8.09 percent. We show that policy effects are driven by individuals living in states that did not have high-risk pools in place prior to 2014, a subgroup most likely to benefit from the federal policy. Additionally, we find that the provision improved the mental well-being of women, while having no effect among men.

In the later part of the study, we examine the role of three potential mechanisms underlying the relationship between the policy change and mental health. First, using data from the American Community Survey (ACS), we provide evidence that the preexisting conditions provision increased insurance coverage among individuals with prior health issues, which is in line with previous work on the provision (Collins et al., 2017; Glied and Jackson, 2017; Department of Health and Human Services, 2017). Second, we show that the policy change reduced health care expenditures and financial strain related to health care costs. For example, we find a reduction of 3.09 percentage points (baseline mean 19.67 percent) in the likelihood of having unpaid medical bills among individuals with preexisting conditions. This is consistent with evidence by Finkelstein et al. (2012) showing that changes in financial strain related to health care expenses are a potential mechanism through which insurance access improves mental health. Finally, we provide evidence that the preexisting conditions provision improved several outcomes related to physical health among individuals with prior health issues. Given that earlier work has found that changes in physical health can impact mental health (e.g. Das et al., 2016; Ohrberger et al., 2017), we believe an improvement in physical well-being can also explain the observed reductions in mental distress.

## 2. ACA PROVISIONS

### 2.1 Preexisting Conditions



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One of the most popular provisions of the ACA was the preexisting conditions provision. The provision was implemented in January 2014 for adults and it guaranteed that people could not be denied insurance coverage or charged higher premiums due to their medical history. While other ACA provisions caused controversy in the years surrounding passage, public opinion regarding the preexisting conditions provision has been generally positive. Using data from 2018, the a recent policy brief shows that over 70 percent of Americans think that insurance companies should be prohibited from denying or charging higher premiums to people with underlying health conditions (Kaiser Family Foundation, 2018).

Despite wide popularity of the preexisting conditions provision, research studying effects of the policy is limited. We are aware of three studies that show that the ACA provision increased access to health insurance coverage among individuals with preexisting conditions (Collins et al., 2017; Glied and Jackson, 2017; Department of Health and Human Services, 2017). The fact that each of these studies uses a different data source further suggests that the ACA provision affected health care access for individuals with underlying conditions. Collins et al. (2017) find that the share of individuals with prior health issues that gained insurance coverage increased by 67 percent between 2010 and 2016, whereas the insurance rate for the entire sample increased by only 44 percent over the same period. Similarly, individuals with prior health issues experienced larger declines in the likelihood of reporting that they are unable to find affordable coverage or find the coverage that they need. Examining data from the Behavioral Risk Factor Surveillance System (BRFSS), Glied and Jackson (2017) show that, among all nonelderly adults who gained insurance coverage, up to 57 percent had prior health issues associated with limited access to coverage.

We are also aware of two prior studies that focus on the preexisting conditions provision for children. Chatterji et al. (2016) compare labor market mobility of parents of



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children with chronic conditions to that of parents of healthy children. The authors find that the preexisting conditions provision improved job mobility among parents of children with health conditions. Similarly, Choudhury et al. (2019) compare children with chronic conditions to children with acute conditions and find improvements in health insurance coverage and inpatient medical care among the chronically-ill.

To the best of our knowledge, Hampton and Lenhart (2019) is the only prior study to look at the provision as it was implemented for adults in 2014. They compare adults with preexisting conditions to those that are healthy and find evidence that the policy led to decreased marriage and increased divorce among those with health issues. To study the impact of the provision on mental health outcomes of adults, we adopt an identification strategy analogous to that of Hampton and Lenhart (2019), which compares individuals with preexisting physical health conditions to those that are relatively healthy.

2.2 Pre-ACA High Risk Pools

In addition to examining the overall effects of the ACA provision on mental health outcomes, we further exploit variation in the presence of pre-ACA high-risk pools. High-risk pools have been in place in some states such as Minnesota and Connecticut as early as 1976, and there are several channels through which an individual could qualify for insurance coverage through a high-risk pool. An individual could be medically eligible, which requires them to demonstrate their application for individual health insurance had been denied or restricted, or that they had been diagnosed with an eligible condition. In about two-thirds of state high-risk pools, an individual could also be a Medicare recipient requiring supplemental coverage (Pollitz, 2017).[4] By the end of 2011, combined enrollment in state high-risk pools was 226,615.

[4] Medicare is a U.S. Social Insurance program providing insurance coverage to the elderly population (ages 65 and up).



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Before the 2014 provision, 35 states had high-risk pools in place, which were set up to provide insurance coverage to individuals with preexisting conditions. The remaining 16 states (including D.C.) had no high-risk pools prior to 2014. Due to this state-level variation in access to coverage, we separately evaluate the effects of the ACA provision on mental distress in states with and without high-risk pools. If the policy change improves mental well-being among people with preexisting conditions, we would expect this effect to be more prevalent in the 16 states that had no high-risk pools in place before the policy.

### 2.3 Other ACA Provisions

In addition to the preexisting conditions provision, the ACA included several other policies that improved access to care for many Americans. Prior to 2014, individual market insurance was not guaranteed to be issued to applicants regardless of health status, age, or income. The ACA effectively changed this with all major insurance plans becoming "guaranteed issue". Furthermore, the ACA included a community rating provision, which prevents health insurance companies from varying premiums within a geographic area based on age, gender, health status, or other factors. In order to provide additional incentives for previously uninsured individuals to obtain coverage, the ACA included an individual mandate that requires all citizens and legal residents of the U.S. to have health insurance. Those ineligible for exemptions who did not comply with the mandate were issued penalties by the Internal Revenue Service (IRS).[5] Additionally, the ACA incorporated the establishment of health insurance exchanges, which provided a marketplace that allowed individuals to choose the type of insurance that best meets their needs.

Another provision of the ACA intended to increase insurance coverage is the employer mandate. Under the Employer Shared Responsibility Provision, applicable large

[5] The tax penalty associated with the individual mandate has since been repealed in 2017.



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employers must either provide affordable, minimum essential coverage to employees or make a shared responsibility payment to the IRS. The intentions of the employer mandate were to increase coverage by ensuring that large employers (50 or more workers) provide insurance coverage for employees. By providing employer-sponsored coverage, employers can avoid paying the shared responsibility payment, which is equal to $2,000 (indexed for future years) for each full-time employee, with the first 30 employees excluded from the calculation (IRS, 2020). The employer mandate went into effect on January 1, 2015. We are aware of one pre-ACA study that evaluates the effects of Hawaii's Prepaid Health Care Act (PHCA), a program that mandates employers to provide health care coverage for employees working more than 20 hours per week over the past two decades, on insurance coverage (Buchmueller et al., 2011). The authors find that the law increased insurance coverage among individuals who were likely to go without coverage in the absence of a mandate, and it is likely that the ACA employer mandate would have a similar affect nationwide.

Yet another component of the ACA that likely increased insurance coverage is the introduction of health insurance marketplace subsidies. In an effort the expand access to affordable health care for individuals with moderate and low income, particularly those without employer-sponsored insurance, Medicaid, or Medicare, the government offered two types of subsidies to marketplace enrollees (Kaiser Family Foundation, 2010). The first, the premium tax credit, reduces enrollees' monthly premium payments for insurance coverage. The second, the cost-sharing reduction, reduces enrollees' out-of-pocket costs when utilizing health care. Along with other pillars of the ACA, these subsidies also likely led to coverage gains, particularly for middle-of-the-road earners who made too much to qualify for Medicaid.[6]

[6] It should be noted that all of the ACA provisions discussed in this section were permanent policy changes that remained in place throughout our sample period. One final provision that was introduced as part of the ACA led to the fact that individuals who smoke tobacco can face significant premium increases of up to 50%.



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These additional provisions that were introduced in 2014 alongside the preexisting conditions provision could have also affected the mental well-being of individuals with prior health conditions. Nonetheless, we believe that the preexisting conditions provision had the largest direct impact on mental distress among this subgroup of the population, given that the provision ensured them access to coverage after years of ineligibility. This is especially the case for individuals living in states that did not have high-risk pools in place prior to 2014.

## 3. PREEXISTING CONDITIONS PROVISION AND MENTAL HEALTH

While there are a number of channels through which health care policy may influence mental health, increasing the availability of affordable insurance and access to appropriate levels of health care may be the most direct path. Mental illness represents a major source of disability in the United States that is often underestimated by the public and health care professionals (Vigo et al., 2016). The World Health Organization defines health as “a state of complete physical, mental, and social well-being, and not merely the absence of disease or infirmity.” Because mental health is essential to overall health and well-being, it must be recognized and treated with the same urgency as physical health (CDC, 2008). Although being recognized as increasingly important following the ACA, access to treatment for mental health issues has not always been a priority in the U.S. While the ACA reforms increased access to health care for many individuals, still less than half of American adults with mental illness received treatment in 2018, while 13.4 percent had no insurance coverage (Substance Abuse and Mental Health Services Administration, 2019).

There is a close link between the insurance status of an individual and access to appropriate mental health services (Institute of Medicine, 2002). Individuals with mental illness are also more likely to experience insurance coverage lapses (Sturm and Wells, 2000) as well as transitions into Medicaid coverage (Rabinowitz et al., 2001). A major goal of the ACA was to decrease the number of uninsured individuals in the U.S. through several major



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pillars including the health insurance exchanges, the dependent coverage provision, and Medicaid expansion. The preexisting conditions provision benefited many people who were previously locked out of the private market, including those excluded because of a documented mental health diagnosis (Mechanic, 2012; Golden and Vail, 2014).

These issues related to access and care are amplified for those with preexisting physical health conditions. Prior to the ACA, an individual with preexisting conditions faced barriers in the procurement of insurance, which may have led to exacerbated levels of mental distress. Not only is insurance often necessary to receive appropriate mental health treatment, having no coverage in itself can lead to worse mental health. Finkelstein et al. (2012) document from the Oregon Medicaid experiment that individuals with generous health insurance are more likely to be happy, and less likely to suffer from depressive symptoms. While the authors provide suggestive evidence that these effects are linked to the alleviation of financial strain created by insurance coverage, they also note that a substantial part of the estimated improvements may reflect a general sense of improved wellbeing.[7]

Another possible mechanism underlying the relationship between the ACA preexisting conditions provision and mental well-being is physical health. This is consistent with findings in previous work showing that improvements in physical health can also lead to better mental health (e.g. Das et al., 2016; Ohrberger et al., 2017). Related to the notion that the policy likely improves access to health care, individuals with prior health issues might be more likely to take care of these existing problems.

We believe that a combination of the above mentioned factors is likely to explain any relationship between the provision and mental distress. While we acknowledge that other

[7] Evidence for this is shown by the fact that Finkelstein et al. (2012) conduct their initial survey at the beginning of the experiment, before any noted increase in health care utilization occurred. Despite questioning participants at an early stage of the experiment, the authors find improvements in self-reported physical and mental health, which they partly attribute to an improved outlook and sense of wellbeing due to gaining insurance coverage.



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possible pathways could also play a role, we examine the role of the following three pathways in this study: 1) health insurance coverage, 2) health care expenditures and financial strain related to health care costs, and 3) physical health.

## 4. DATA

This study uses data from the Panel Study of Income Dynamics (PSID). The PSID began in 1968 with a nationally representative sample of more than 18,000 individuals from 5,000 U.S. households. Interviews were conducted annually from 1968-1997, and biannually since 1997. We follow the same individuals between the years 2007 and 2017, which provides our analysis with four waves prior to and two waves after the 2014 policy. In our main analysis, we restrict the sample to respondents who are present in all five PSID waves. To address potential concerns of sample attrition that could occur if individuals with preexisting conditions are more likely to drop out of the survey, we also estimate specifications including individuals that are not present in all waves. To limit the analysis to working-aged adults, we restrict the sample to those ages 18-64. Additionally, we exclude individuals with no information regarding their mental health. Overall, sample restrictions leave our main analysis with 13,849 individuals and 69,245 total observations.

The main outcome variable studied in this paper is the Kessler K6 nonspecific distress scale, which provides a screening for the presence of both moderate and severe mental distress. The K6 score is comprised of a series of six survey questions related to mental distress. These questions include information on how respondents felt over the 30 days prior to the interview. Specifically, individuals are asked how often they felt so sad that nothing could cheer them up, nervous, restless/fidgety, hopeless, worthless, and that everything is an effort. The responses are never, a little of the time, some of the time, most of the time, or all of the time, which are coded as a value of 0, 1, 2, 3, or 4, respectively. Responses to the six items are summed to yield a K6 score between 0 and 24, with higher scores indicating more



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severe mental health issues. Using standard cutoffs (e.g. Furukawa et al., 2003; Kessler et al., 2003; Pratt, 2009; Prochaska et al., 2012; Kim et al., 2012 and 2016; Forman-Hoffman et al., 2014), individuals with a K6 score greater than twelve are classified as having severe mental distress. As pointed out by Forman-Hoffman et al. (2014), a score of 13 or higher is a strong indicator of the presence of a diagnosable mental illness with considerable disability.[8] Along with evaluating the effects of the policy on mental distress, in additional analyses we test for the role of financial strain related to medical expenditures as a potential channel. Following Finkelstein et al. (2012), we evaluate the effects on the likelihood of having unpaid medical bills.

To study a group of individuals likely impacted by the preexisting conditions provision, we use self-reported responses to whether an individual has ever been diagnosed with a series of physical health conditions by a doctor or another health professional including stroke, heart attack, heart disease, lung disease, diabetes, cancer, seizures, kidney disease, autoimmune disorder, Parkinson's disease, coronary problems, and bone disorder.[9] By providing an overview of the most common conditions that led to a denial of insurance coverage prior to the ACA, Fehr et al. (2018) list all the PSID conditions that we use in our analysis. Similarly, in a review obtained from 12 major health insurance providers in the U.S., Claxton et al. (2019) show that these conditions would have likely led to coverage denial or higher premiums prior to the ACA.

The main treatment group in the analysis consists of individuals reporting that they suffered from at least one of the conditions in all three pre-policy survey years (1,950 individuals and 9,750 observations). Individuals who have no preexisting conditions in any of

[8] In alternative specification, we use three different K6 cutoffs to test whether the findings are robust to the choice alternative cutoffs to measure mental distress.
[9] These are the same preexisting conditions defined by Hampton and Lenhart (2019).

the three pre-policy waves (11,899 individuals and 59,495 observations) form the control group.

We conduct additional analysis of health insurance coverage gains of those with underlying health conditions using an additional data source, the American Community Survey (ACS).[10] The ACS is a nationwide survey conducted continuously throughout each year containing information on approximately 3 million households annually. The cross-sectional dataset contains information on whether or not a respondent has health insurance coverage. While the survey does not contain specific physical health questions such as those available in the PSID, we rely on an indicator for whether a person has a disability to create treatment and control groups. In our analysis of health insurance coverage, we define individuals with a disability as treated, and those without a disability as the control group. While this is not a perfect substitute for our more detailed definitions using PSID data, we argue that individuals with disabilities are more likely to be impacted by the ACA preexisting conditions provision than those without. In our analysis of ACS data, we include the same control variables as available in the PSID.

When examining the role of health-related expenditures, we use six different outcomes that are available in the PSID: 1) an indicator that equals one if respondents have any medical debt; 2) total out-of-pocket health expenditures; 3) total health insurance expenditures; 4) total out-of-pocket doctor expenditures; 5) total out-of-pocket expenditures on prescriptions and in-home medical care; and 6) total out-of-pocket expenditures on hospital bills and nursing homes. We also evaluate the effects of the provision on physical health, which we capture by the following five outcomes available in the PSID: 1) fair/poor

[10] The PSID is less than ideal for conducting an analysis of insurance coverage gains due changes over time in survey methodology related to variables assessing health insurance coverage.

health status; 2) excellent/very good health status; 3) health limits the type or amount of work; 4) missed work due to illness in the past year; 5) have difficulty walking.

## 5. METHODS

### 5.1 DD Analysis

Our empirical strategy uses a difference-in-differences (DD) method to test the impact of the ACA preexisting conditions provision on mental distress. In the main analysis, we compare changes in levels of mental distress among individuals with preexisting physical health issues to healthy individuals (first difference) before and after the implementation of the provision (second difference). Exploiting state-level variation in the presence of high-risk pools prior to the ACA, we separately evaluate the effects of the policy on two groups of states: 1) the 35 states that had high-risk pools in place prior to 2014; and 2) the 16 states (including D.C.) that did not have high-risk pools. Appendix Table A1 provides an overview of which states belonged to the two groups.[11] If access to insurance coverage affects mental well-being, we would expect to find larger effects in the second group of states since increases in coverage among individuals with preexisting conditions is likely substantially larger in these states.

Given that there are substantial gender differences in the prevalence of mental health issues (Substance Abuse and Mental Health Services Administration, 2019), we also present estimates for males and females separately. It has been shown that women are more likely than men to delay health care due to cost (Kaiser Family Foundation, 2013). Thus, there may be differential effects of the policy on mental health for women and men.

[11] Table A1 also provides information on which states expanded their Medicaid programs during the period of our study. The table shows that Medicaid expansions occurred in both states with and without pre-ACA high risk pools. Of the 35 states with such pools, 14 expanded their Medicaid programs, while 6 of the 16 states without high risk pools had implemented Medicaid expansions during the period of our study.

Our main outcome of interest is an indicator of severe mental distress. Given that the PSID is a longitudinal dataset, we are able to track the same individuals over time and study changes in mental distress throughout the period of study. The identifying variation in our analysis, which is the same studied by Hampton and Lenhart (2019), exploits differences in the presence of preexisting conditions across individuals. The baseline model that measures the impact of the ACA preexisting conditions provision on mental health outcomes is:

$$Y_{ist} = \beta_0 + \delta_{DD}\ Post_{ist} * Condition_i + \beta_1\ X_{ist} + \beta_2\ Z_{st} + \lambda_1\ Year_t + \lambda_2\ State_s + \alpha_i + \varepsilon_{ist}, \quad (1)$$

where $Y_{ist}$ represents the main outcome variable, which is an indicator equaling one if individual i living in state s at time t is experiencing severe mental distress. Given that the ACA preexisting conditions provision was implemented in 2014 for adults, $Post_{ist}$ is an indicator for the post-treatment period (2015 and 2017). $Condition_i$ is an indicator capturing whether individuals belong to the treatment group, i.e., they have preexisting conditions in all four pre-policy waves (2007, 2009, 2011, and 2013). The DD coefficient of interest, $\delta_{DD}$, measures the effect of the policy on mental distress. We control for observable characteristics, denoted by $X_{ist}$, including the number of children in the household, the number of years of completed education, and employment status. $Z_{st}$ accounts for state-level variations in the implementation of the following ACA provisions and other policy changes: 1) Medicaid expansions; 2) Community First Choice Medicaid options, which allow states to provide community-based support for individuals with disabilities; 3) Home and community-based services, which give states additional options for providing home and community services through Medicaid state plans, primarily for people with mental health needs; 4) an indicator for whether states allow the sale of "grandfathered" insurance plans that had been in existence prior to the ACA; and 5) state-level dependent coverage mandate laws.

Several features of the model above warrant further discussion. First, the model includes state fixed effects to account for time-invariant state-specific differences in mental


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distress levels, and year fixed effects to control for unobservable characteristics across time that may affect the outcomes of interest.[12] Additionally, as the PSID data is longitudinal, it allows us to include individual-level fixed effects, denoted by $\alpha_i$, to account for unobserved heterogeneity at the person-level. Furthermore, inclusion of the individual-level fixed effect controls for the fact that each respondent may have their own scale in rating mental distress by comparing each individual's mental distress to their own prior assessment (reference bias). Our estimation uses ordinary least squares, with standard errors clustered at the state level to account for correlated error terms across states over time.[13]

Identification in the DD model is based on the assumption of parallel trends, i.e., absent of the 2014 ACA preexisting conditions provision, trends in outcomes would not have differed significantly across individuals with and without preexisting conditions. While it is impossible to test this assumption directly, we graphically compare trends in mental distress across preexisting conditions status prior to the change in policy (Figures 1a-b). Figure 1a shows that individuals in the treatment group are more likely to experience severe mental distress throughout the study period, while the gap becomes smaller after 2014 due to a decline in mental distress among the treatment group. The graph shows that there are some fluctuations in the pre-2014 periods among treated individuals. We believe this is associated with two factors. First, as suggested by differences in descriptive statistics (e.g. employment and medical debt) between the two group, the Great Recession likely had a larger effect on mental well-being for individuals in the treatment group.[14] Second, we believe that the noise in the pre-2014 data could be explained by a combination of the relatively small sample size and the fact that mental distress is self-reported. To account for the small sample size, we

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[12] In some specifications, we also include state-specific, linear time trends.
[13] While we do not apply sample weights in our main analysis, we apply longitudinal PSID sample weights in additional specifications.
[14] We also find that the increase in mental distress between 2007 and 2009 is driven by individuals living in states that had no pre-ACA high-risk pools.

additionally estimate specifications that relax the sample restrictions to increase the number of individuals. Rather than only considering individuals as treated if they report a preexisting condition in all four pre-2014 waves, we include individuals as treated if they had a condition in at least two pre-2014 waves in these additional restrictions. Figure 1b shows changes in mental distress for this larger sample. While we still observe a reduction in mental distress among treated individuals after the policy change, the graph provides suggestive evidence for the presence of parallel trends between the two groups prior to 2014.

To further account for potentially different trends between treatment and control groups during the pre-treatment period, we also estimate an alternative DD specifications that include several alternative parallel trends assumption (Mora and Reggio, 2019). We provide more details on this DD model in the next subsection.

Due to the setup of our DD models, which compare individuals with and without preexisting health conditions, our analysis only has two clusters. As suggested in the literature, this implies that we need to include small-cluster corrections in our analysis. We calculate p-values using the wild cluster bootstrap resampling method with 1,000 replications, proposed by Cameron et al. (2008), which performs well with a small number of clusters. Additionally, we apply the 6-point distribution suggested by Webb (2014) and MacKinnon and Webb (2017). As the authors point out, the main advantage of this 6-point distribution bootstrap weight is that it increases the number of potential bootstrap samples exponentially compared to a Rademacher distribution, which works well for a larger number of clusters.

To provide additional evidence that trends in outcomes of interest did not differ prior to the 2014 implementation and to test for year-by-year effects of the policy, we augment Equation (1) to reflect an event study of the form:

$$Y_{ist} = \beta_0 + \sum_{t=2009}^{2017} \delta t \text{ Year}_t{}^* \text{ Condition}_i + \beta_1 X_{ist} + \beta_2 Z_{st} + \lambda_1 \text{ Year}_t + \lambda_2 \text{ State}_s + \alpha_i + \varepsilon_{ist}, \quad (2)$$

where $\delta_t$ estimates heterogeneous effects of the policy across panel years 2007-2017 (in this analysis, the year 2007 is excluded as a reference category). Not only does the event study specification of Equation (2) allow the effect of the policy to vary across time (which distinguishes between contemporaneous and lagged effects), it also allows for further testing of the DD parallel trends assumption. If $\delta_t$ is estimated to be statistically indistinguishable from zero in the panel years prior to 2014, then this implies that there were no statistical differences between treatment and control groups prior to the ACA, which further supports the validity of the DD approach.

5.2 Alternative DD Model (Mora and Reggio, 2019)

DD models require an assumption that trends in the variable of interest are similar for both treatment and control groups in the absence of the policy. This assumption implies that without the treatment, differences between the groups are assumed to be time-invariant. Mora and Reggio (2019) point out that the identification of the treatment effect does not only depend on the parallel trends assumption, but also on the trend modelling strategy applied by researchers. For example, the authors show that DD estimates will differ substantially depending on whether group-specific linear trends or group-specific, time-invariant linear trends are included in the analysis in order to accommodate for trend differentials between treatment and control groups. By arguing that researchers often overlook this fact, Mora and Reggio (2019) introduce an alternative DD estimator, which identifies the effect of the policy using a fully-flexible dynamic specification and includes a family of alternative parallel trends assumptions. This alternative DD model is estimated in two steps (Mora and Reggio, 2019): first, standard least-squares estimation of the fully flexible model is conducted, and second, the solution of the equation in differences identifies the estimates. The computation of the standard errors of the treatment effect estimates takes into account that the solution of the equation in differences is a linear combination of the parameters of the fully flexible model.

The two main advantages the authors list in favor of their DD estimate are that it: 1) allows for flexible dynamics and for testing restrictions on these dynamics; 2) does not impose equivalence between alternative parallel assumptions. Estimating this alternative model can lend support to the validity of standard DD assumptions if the results are in line with the main DD estimates.

5.3 DDD Analysis

One way to test for the presence of any bias in the DD analysis related to other changes across treatment and control groups is to additionally estimate DDD models that take into account that states with and without high-risk pools prior to 2014 were differentially affected by the preexisting conditions provision. The 16 states that had no high-risk pools in place prior to 2014 are likely to be affected substantially more than the 35 states that had high-risk pools. Specifically, we estimate the following equation:

$$Y_{ist} = \beta_0 + \delta_{DD}\ Post_{ist} * Condition_i * NoPool_s + \beta_1\ Condition_i * Post_{ist} + \beta_2 Condition_i * NoPool_s + \beta_3\ NoPool_s * Post_{ist} + \beta_4\ NoPool_s + \beta_5\ X_{ist} + \beta_6\ Z_{st} + \lambda_1\ Year_t + \lambda_2\ State_s + \alpha_i + \varepsilon_{ist}, \quad (3),$$

where $NoPool_s$ is an indicator that equals one if the state had no high-risk pool in place prior to 2014, and zero otherwise. While all other variables remain the same as in equation (1), the main parameter of interest for estimating equation (2) is $\delta_{DDD}$.

5.4 Descriptive Statistics

Table 1 provides descriptive statistics for the treatment and control groups of the sample. While the two groups are very similar in terms of gender, marital status, race, and education, treated individuals are on average older, less likely to work, and have fewer children living with them.[15] Individuals with preexisting conditions are twice as likely to have unpaid medical bills (18% vs 9%) than those without any preexisting conditions. Among the treatment group, the statistics for different types of preexisting conditions show that diabetes is the most common condition, followed by lung disease, heart disease, and cancer. Appendix Table A2 presents descriptive statistics from the ACS sample.

Table 2 presents descriptive statistics for all measures of mental distress used in our analysis. While treated individuals are more likely to experience severe mental distress before and after the policy, the gap between the two groups narrows in the post-ACA years. Table 2 also shows statistics for each of the six components of the K6 mental distress index. It is noticeable that all six measures of mental well-being improved in the post-policy period for treated individuals. For four of the six measures, there is a noticeable narrowing of the gap between treatment and control groups.

## 6. RESULTS

### 6.1 Effects on Mental Distress

Table 3 shows intent-to-treat effects on the likelihood of experiencing severe mental distress (K6 score between 13 and 24) for the full sample, and separately for individuals living in states with and without high-risk pools prior to 2014. We find that the policy reduced the likelihood of severe mental distress by 1.43 percentage points ($p<0.01$) of the entire sample, which corresponds to a change of 17.68 percent compared to the pre-policy baseline mean (8.09 percent). This estimate remains robust when adding control variables to the model as well as state-specific time trends.[16]

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[15] The fact that around 70% of the individuals in our sample are male can be explained by the structure of the PSID. The survey interviews household heads, which it assumes to be male in married households.

[16] While this effect appears large in magnitude, it should be noted that the upper tails of the 95% confidence intervals for the full sample estimates in Table 3 are between -0.0033 and -0.0046. In the conclusion of the paper, we provide a discussion showing that our estimates are comparable with previous work evaluating the association between newly gained access to health insurance coverage and mental well-being.

When examining whether the provision differentially affected mental distress of individuals in states with and without high-risk pools, we find that the effects observed for the full sample are entirely driven by individuals living in the 16 states that had no such pools. For these states, we find that the ACA preexisting conditions provision reduced the likelihood of severe mental distress by 3.32 percentage points ($p<0.01$) among respondents forming the treatment group. This corresponds to a substantial effect compared to the pre-policy baseline mean of 8.60 percent. In contrast, we find a nil effect among the 35 states that made health insurance available to individuals with preexisting health conditions before 2014. While the ACA included several provisions that could have improved access to care among individuals with preexisting conditions, the results in Table 3 provide evidence that the preexisting conditions provision specifically is responsible for reductions in mental distress. Given that many individuals with prior health conditions living in states with high-risk pools had access to health insurance before 2014, finding significant effects only in states without high-risk pools suggests that increased access to insurance coverage led to improvements in mental well-being.[17]

Table 4 provides the intent-to-treat estimates obtained from estimating DDD models. In line with the results in Table 3 showing that the observed improvements in mental distress are driven by individuals living in states that had no high risk pools in place prior to 2014, our DDD estimate shows a 3.31 percentage point reduction ($p<0.01$) in severe mental distress.

Figure 2 shows the event study estimates for our analysis. Using 2007 as the reference period, the graph provides evidence for negative effects in the two post-2014 periods. While not showing differential effects across the groups in the two waves prior to the policy change

[17] Appendix Table A3 shows that the estimates remain very similar when excluding state fixed effects from the models. Thus, the findings indicate that our main findings in Table 3 are not driven by a possible high collinearity between individual and state fixed effects.

(2011 and 2013), Figure 2 shows a positive effect in 2009. We believe that this difference in mental distress between the two groups is related to the onset of the Great Recession.

Table 5 shows the estimates that we obtain when estimating the alternative DD model introduced by Mora and Reggio (2019). When comparing these results with the main DD results in Table 3, it is noticeable that the effects remain similar. Again, we find that the policy change reduced mental distressed among individuals with preexisting health conditions, and that these effects are driven by those who live in states that did not have pre-ACA high risk pools. The magnitudes of the effects remain similar across the two DD models. The fact that the results remain similar despite the additional DD assumptions based on the number of pre-treatment periods in the Mora and Reggio (2019) model provides additional validity to the main DD analysis and the parallel trends assumption.

While Tables 3-5 provide evidence of the effects of the policy on mental distress using all K6 score questions, Table 6 shows estimates for all six survey questions separately. We find that individuals with preexisting conditions are 1.09 percentage points ($p<0.01$) less likely to report that they feel hopeless. It seems reasonable that this decline could be related to the fact that the provision reduced financial stress and uncertainty related to health care expenditures. Interestingly, Table 6 shows a statistically significant increase in feeling that everything is an effort ($p<0.05$). We believe that there could be two possible explanation for this somewhat contrary finding. First, it has been shown that individuals do not understand their insurance plans and find the difficult to use due to complex language and a complicated pricing system (Arora et al., 2015). Second, related to previous work showing that the preexisting conditions provision reduced the likelihood that individuals with prior health issues remained married (Hampton and Lenhart, 2019), people might be more likely to report that everything is an effort following a divorce due to increased responsibilities in the



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household. As shown in Table 6, we find negative but imprecisely estimated effects of the policy change for the remaining four emotions that are used to obtain the K-6 score.

Table 7 presents gender-specific DD effects of the preexisting conditions provision on mental distress. The results show that the reductions in mental distress observed in our main analysis are entirely driven by improvements in mental well-being among women. While finding nil effects among men, we find that the policy change reduced the likelihood of women with preexisting conditions experiencing severe mental distress by 3.08 percentage points ($p<0.01$), which corresponds to a decline of 20.75 percent. In light of previous work showing that the preexisting conditions provision improved access to insurance coverage (Collins et al., 2017; Glied and Jackson, 2017; Department of Health and Human Services, 2017), the gender-specific results In Table 7 are in line with other studies suggesting that women are more likely to delay health care due to cost (Kaiser Family Foundation, 2013).

## 6.2. Robustness Checks

In this section, we present findings from several additional specifications that examine whether the main estimates are robust to specific assumptions made in the sample and data selection. While our specifications in the previous section do not include any weights, Appendix Table A4 provides DD estimates obtained when including longitudinal PSID sample weights. We find that the results are consistent with the estimates in Table 3. Appendix Table A5 shows that our findings are also robust to the use of alternative cutoffs for mental distress. For all three new cutoff points, we find statistically significant declines in mental distress. Appendix Table A6 shows that, while substantially smaller in magnitude, we still find statistically significant reductions in mental distress when relaxing the treatment group criteria by considering all individuals who report having had a preexisting condition in at least two out of four pre-2014 survey waves as treated. We also show that the results are robust to accounting for sample attrition by including individuals who are not present in all



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five survey waves.[18] In an additional robustness check, we estimate several additional specifications removing and adding new covariates to the main DD models. The results, which are presented in Appendix Table A7, show that our main effects are robust to both the exclusion and inclusion of covariates.

Finally, in Appendix Table A8, we show the results for an alternative DD specification, where we limit the sample to individuals who did not have any preexisting conditions in the pre-2014 period. We use an indicator for being in either fair or poor health prior to 2014 as the treatment group status indicator, meaning that individuals with either excellent, very good, or good health status prior to 2014 form the control group. While the two groups used in this specification differ in terms of self-reported health status, they should not be differentially impacted by the ACA preexisting conditions provision. Thus, this alternative specification serves as a falsification test. The results show that we find small and statistically insignificant effects, which furthermore suggests that our main findings are driven by the preexisting conditions provision.

### 6.3 Mechanisms

To understand the potential mechanisms through which the preexisting conditions provision improves mental health, we estimate the effects of the provision on health insurance, health care expenditures, and physical health.

#### 6.3.1 Health Insurance

Using ACS data, Figure 3 shows the proportion of individuals with insurance coverage before and after the ACA preexisting conditions provision implementation for the treatment and control groups. The figure shows that individuals with a disability are less

[18] The estimated intent-to-treat effects remain very similar when including individuals who are not present in all five waves of the sample period. Attrition rates are actually slightly larger for individuals in the control group.



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likely to be insured throughout the study period, a reflection of the difficulty in attaining insurance coverage for those with underlying health problems. While both groups observe coverage gains following 2014, the gains for treated individuals are more pronounced and thus, a narrowing of the gap between the treatment and control groups can be observed.

To more formally assess the impact of the ACA preexisting conditions provision on coverage gains of individuals with health conditions, Table 8 shows DD estimates. The dependent variable of the model is an indicator for whether a person has health insurance coverage. From column 2, individuals with a disability are 0.38 percentage points ($p<0.01$) more likely to have insurance coverage following the policy change. This finding is in line with previous work on the preexisting conditions provision (Collins et al., 2017; Glied and Jackson, 2017; Department of Health and Human Services, 2017). Table 8 furthermore shows separate effects for states with and without high-risk pools, respectively. While treated individuals observe coverage gains in both sets of states, the coefficients are about twice as large in magnitude in states that did not offer high-risk pools prior to the ACA. This is consistent with our findings that reductions in mental distress were largest in states without any high-risk pools prior to 2014.[19] Given that many individuals with preexisting conditons

[19] In additional specifications, we test whether the policy change led to state-level migration among individuals with preexisting condtions. The results are presented in Appendix Table A9 and provide suggestive evidence that people with prior health issues were more likely to move to a different state after the provision was implemented. However, due to the small number of individuals in our treatment group who move between waves, we believe these results could be due to noisy data and thus should be viewed with caution since. Our main treatment group consists of 1,950 individuals who we follow throughout the study period (2007 to 2017). Our data indicates that, on average, around 50-60 individuals from the treatment group migrate to a different state between two waves. While the number of "movers" is larger in the control group (around 700 individuals on average between waves), the share of people moving to a different state is very similar across the two groups. One explanation for the increase in migration could be related to the finding that individuals with preexisting conditions are less likely to remain married following implementation of the provision in 2014, as shown in previous work (Hampton and Lenhart, 2019). We believe that migration could be a pathway through which the policy change improves mental well-being, and be related to job lock and job mobility. While an analysis of these outcomes is outside the scope of this paper, future work should evaluate the association between the policy change and job mobility and migration. Given the small number of movers in the PSID who have a preexisting condition, the use of a larger data set such as the American Community Survey (ACS) might be preferred.



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who could have been denied coverage prior to the ACA might not be captured with our treatment indicator in the ACS data (because they do not have any disabilities), we believe that the finding in Table 8 is a plausible lower bound estimate for the effect of the provision on insurance coverage.

### 6.3.2 Health Care Expenditures

Table 9 presents our DD estimates on the effects of the provision on health care expenditures and financial strain related to health care costs. We find that the policy change reduced the likelihood of having any medical debt by 3.09 percentage points ($p<0.01$) among individuals with preexisting conditions, which corresponds to a 15.7 percent reduction compared to the pre-policy period. This estimate is in line with Finkelstein et al. (2012) who show that access to public insurance coverage reduced the likelihood of having medical collections by about 25 percent. Appendix Table A10 shows that, similar to the effects on mental distress, the reductions in unpaid medical bills following the provision are almost entirely pronounced among women with preexisting conditions. While the estimates for the five measures of household health expenditures are imprecisely estimated, they all show that the provision reduced out-of-pocket expenditures among individuals in the treatment group. Overall, Table 9 provides suggestive evidence that the ACA preexisting conditions provision eased financial strain related to medical expenditures among individuals with underlying conditions, and this could be an explanation for why the reform led to subsequent improvements in mental well-being.

### 6.3.3. Physical Health

Next, we evaluate five outcomes related to physical health. The results for these additional specifications are presented in Table 10. Across all measures, we find that the ACA provision significantly improved physical health outcomes among individuals with preexisting conditions. For example, we show that the policy reduced the likelihood of reporting fair or poor health by 9.15 percentage points ($p<0.01$, 23 percent reduction) and reduced the likelihood of being limited at work due to health issues by 5.98 percentage points ($p<0.01$, 16 percent reduction). Thus, the findings in Table 10 provide suggestive evidence that improvements in physical health could be another pathway through which the provision positively affected mental well-being. This is consistent with evidence in prior studies showing that past physical health can explain current mental health (Ohrberger et al., 2017) and that mental health conditions are more prevalent among people with long-term physical health problems (Das et al., 2016).

## 7. CONCLUSION

The results of our analysis indicate that the ACA preexisting conditions provision led to improvements in mental health. Specifically, following the 2014 policy implementation, individuals with physical health conditions were 1.43 percentage points less likely to suffer from severe mental distress. Subgroup analysis reveals that the treatment effects are driven by individuals with preexisting conditions living in the 16 states that had no high-risk pools in place prior to 2014 as well as by women. When examining potential channels underlying the link between the provision and mental distress, we provide evidence that insurance coverage, health care expenditures, and physical health can explain the observed improvements in mental well-being among the treatment group. An additional potential mechanism is increased utilization of mental health care services. While our study does not include an analysis of this outcome, future research on the relationship between ACA provisions and mental health should examine this in more detail.



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Our main intent-to-treat estimate of this study suggests that the preexisting conditions provision reduced the likelihood of experiencing severe mental distress by 17.68 percent. While this result appears large in magnitude, they are consistent with previous estimates for the effects of access to insurance on mental well-being. Giuntella and Lonsky (2020) find that increased insurance coverage and reduced delay of care due to financial restrictions as a result of the 2012 Deferred Action for Childhood Arrivals (DACA) initiative reduced the likelihood of moderate/serious mental distress by 20 percent. Furthermore, when examining a sample of low-income individuals, the authors find that the effects increase to 29 percent. McMorrow et al. (2016) find that the Medicaid expansions between 1997 and 2009 reduce the likelihood of suffering from moderate mental distress by 21 percent, while Winkelman and Chang (2017) show that the ACA Medicaid expansion reduced the diagnosis of depression and the number of days in poor mental health by 9 and 11 percent, respectively. Estimating intent-to-treat effects of gaining access to Social Security Disability Insurance (SSDI), Weathers II and Stegman (2012) find reductions in SF-36 mental health scores that are indicative of depression by 14 percent.

A potential limitation of our analysis is that the estimates represent regressions to the mean in the wake of an earlier serious health shock. This would suggest that the observed changes in mental distress and medical debt are due to individuals recovering from the shock of the onset of their preexisting condition. In our analysis, individuals are selected into the treatment group if they have ever been diagnosed with at least one preexisting condition due to the fact that the PSID does not have information on the precise timing of the onset of these conditions. It should be noted that individuals could be denied insurance coverage prior to 2014 if they had a preexisting condition, independent of how long they had been dealing with the condition.



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Overall, our results provide evidence for improved mental health following the 2014 ACA provision. While this suggests the overhaul of the health care system had important benefits to society, researchers and policymakers should continue to analyze the health reform to develop a more complete understanding of its intended and unintended results. Given that less than half of individuals suffering from mental illness received treatment in 2018 (Substance Abuse and Mental Health Services Administration, 2019), our study highlights the role of providing access to insurance coverage in order to reduce the share of Americans with mental health problems in the future.

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**Figure 1a: Severe Mental Distress over Time (Main Sample)**

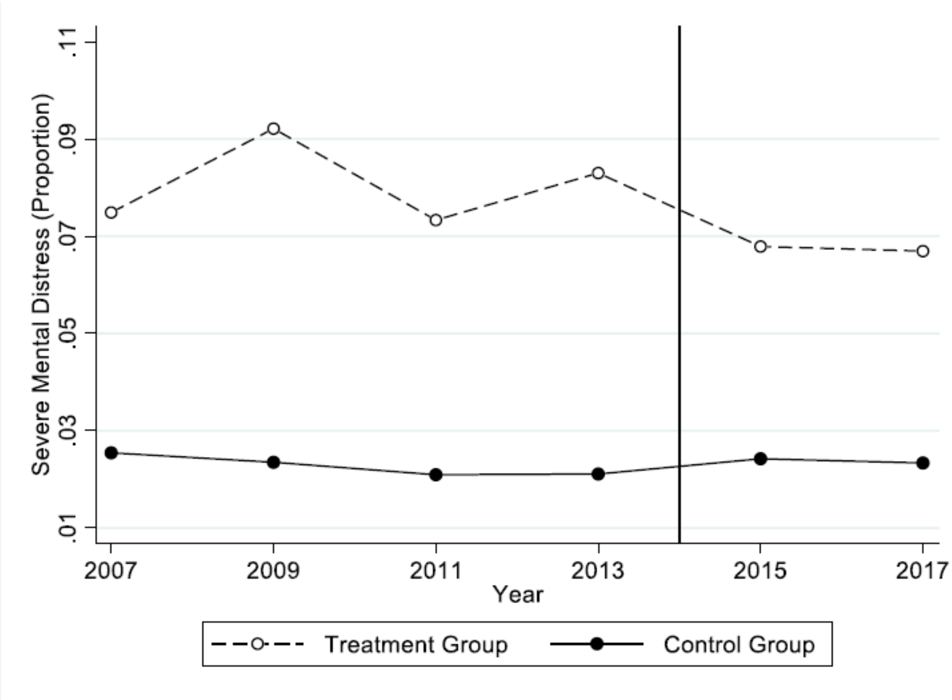
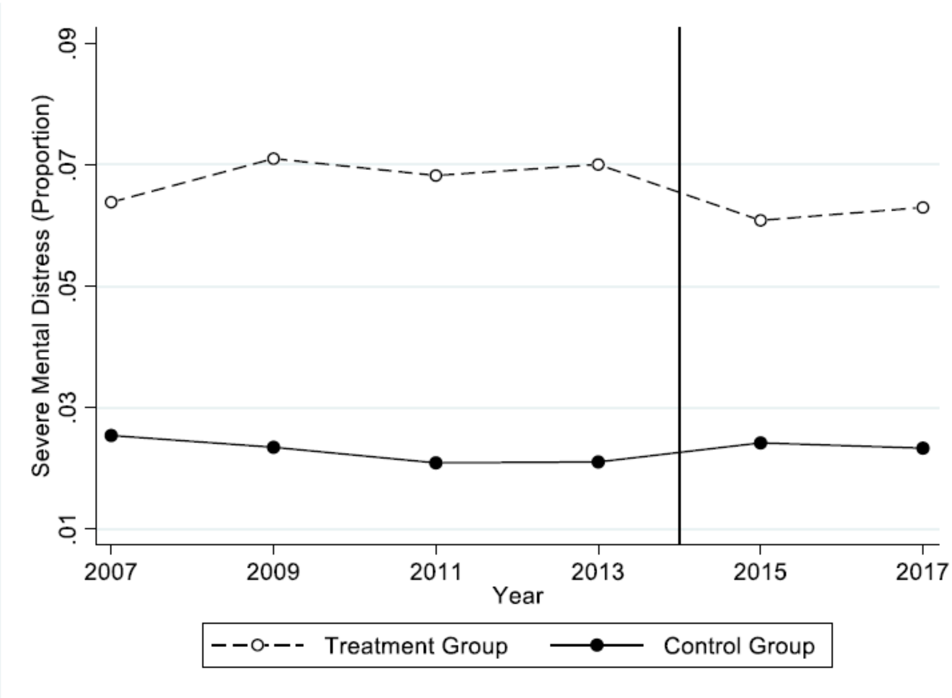



**Figure 1b: Severe Mental Distress over Time (Less Restrictive Sample)**




The figures shows the share of individuals in the two groups that report experiencing severe mental distress during the study period. The main sample in Figure 1a includes individuals with preexisting conditions in all four pre-2014 waves as treated, while the less restrictive sample in Figure 1b includes all individuals with a health condition in at least two of the four pre-2014 waves.



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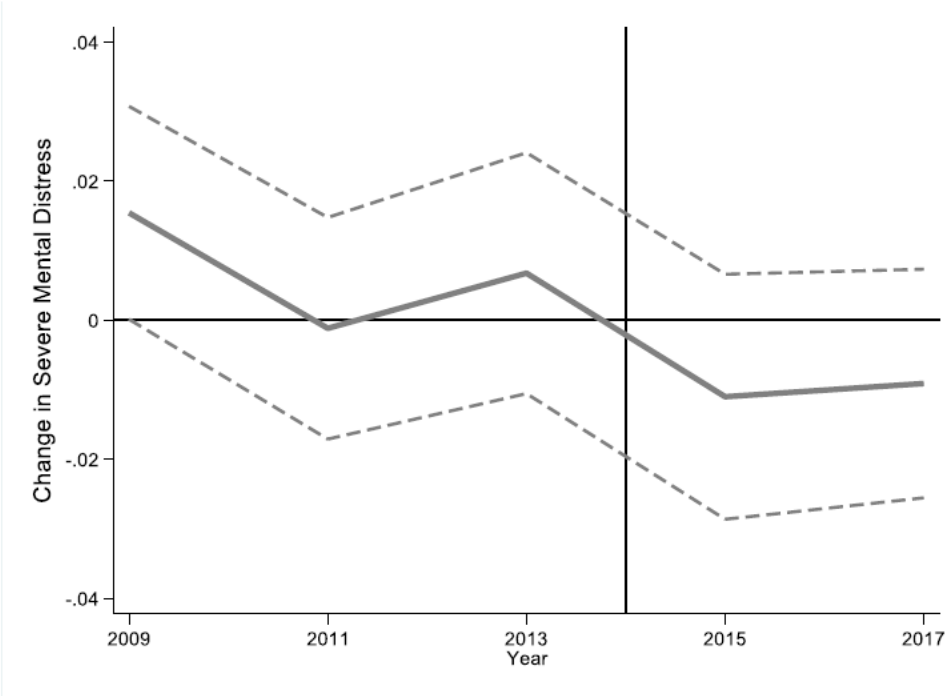
**Figure 2: Annual Treatment Effects**




Note: The dotted line represents the 95% confidence intervals.



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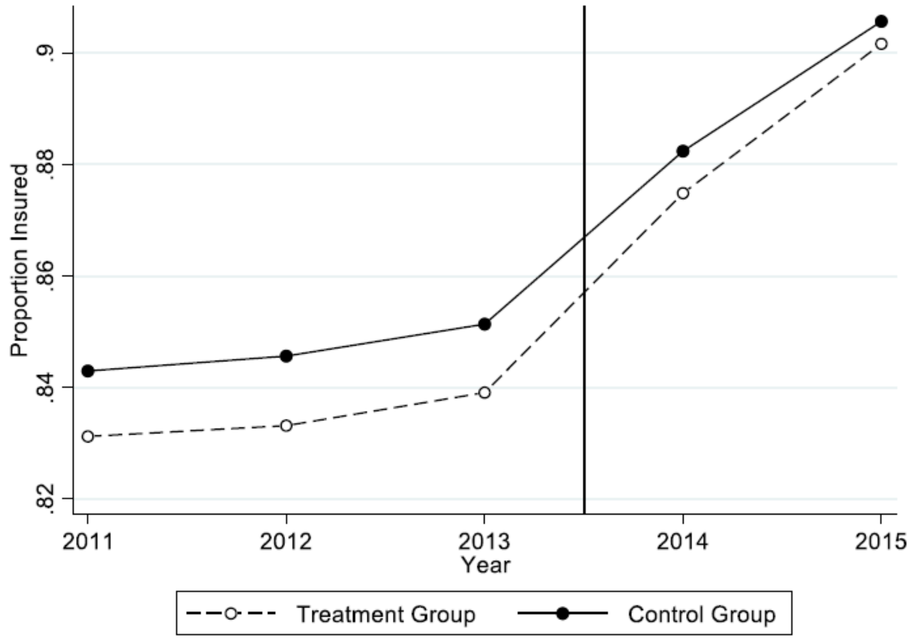
**Figure 3: Health Insurance Coverage Over Time**




The figure shows the share of individuals in the two groups that have any insurance coverage during the study period.



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Table 1: Descriptive Statistics

| | **Treatment Group** | **Control Group** |
|---|---|---|
| Age | 46.245 (10.609) | 38.367 (10.253) |
| Male | 0.702 | 0.7337 |
| Married | 0.560 | 0.5625 |
| Working | 0.616 | 0.8412 |
| Unemployed | 0.060 | 0.0916 |
| # Children in HH | 1.194 (1.472) | 1.518 (1.435) |
| White | 0.565 | 0.5300 |
| Black | 0.385 | 0.4027 |
| At most 12 years of education | 0.503 | 0.4532 |
| >12 years of education | 0.4970 | 0.5468 |
| Have unpaid medical bills | 0.1634 | 0.0864 |
| Stroke (pre) | 0.1020 | - |
| Heart attack (pre) | 0.1385 | - |
| Heart disease (pre) | 0.1645 | - |
| Lung disease (pre) | 0.1394 | - |
| Diabetes (pre) | 0.4398 | - |
| Cancer (pre) | 0.1491 | - |
| N | 8,544 | 61,824 |

The table presents descriptive statistics for the main variables used in the study for the two groups of the study.

Table 2: Descriptive Statistics - Mental Distress

| | **Treatment Group** | **Control Group** |
|---|---|---|
| *N* | *8,544* | *61,824* |
| **Severe mental distress** | | |
| *Pre* | 0.081 | 0.023 |
| *Post* | 0.067 | 0.024 |
| **Sadness** | | |
| *Pre* | 0.059 | 0.025 |
| *Post* | 0.052 | 0.019 |
| **Nervous** | | |
| *Pre* | 0.084 | 0.030 |
| *Post* | 0.073 | 0.024 |
| **Restless** | | |
| *Pre* | 0.113 | 0.052 |
| *Post* | 0.100 | 0.040 |
| **Hopeless** | | |
| *Pre* | 0.046 | 0.013 |
| *Post* | 0.034 | 0.013 |
| **Everything an effort** | | |
| *Pre* | 0.144 | 0.111 |
| *Post* | 0.137 | 0.090 |
| **Worthless** | | |
| *Pre* | 0.036 | 0.010 |
| *Post* | 0.032 | 0.009 |

The table presents descriptive statistics for all six emotions that are included in the Kessler K6 nonspecific distress scale for both groups before and after the 2014 policy change.

Table 3: The Effects of the Policy Change on Severe Mental Distress (DD Models)

| **Treatment Effects** | **Severe Mental Distress** | | | **N** | **Sample Mean** |
|---|---|---|---|---|---|
| Full Sample | -0.0143** | -0.0144*** | -0.0155*** | 70,368 | 0.0809 |
| *Wild Cluster Bootstrap P-Value* | [0.014] | [0.010] | [0.007] | | |
| States with High-Risk Pools (pre-2014) | -0.0002 | -0.0001 | -0.0018 | 49,338 | 0.0784 |
| *Wild Cluster Bootstrap P-Value* | [0.987] | [0.996] | [0.862] | | |
| States w/o High-Risk Pools (pre-2014) | -0.0332*** | -0.0326*** | -0.0317*** | 20,654 | 0.0860 |
| *Wild Cluster Bootstrap P-Value* | [0.000] | [0.000] | [0.001] | | |
| Fixed effects | x | x | x | | |
| Control variables | | x | x | | |
| State-specific time trends | | | x | | |

The results provides DD treatment effects obtained from estimating tbe effects of the preexisting conditions provision on the likelihood of experiencing severe mental distress. All specification use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008), while also implementing a 6-point distribution as introduced Webb (2014) to further account for the small number of clusters. The control variables include age, education, employment status, the number of children living in the household, as well as other ACA provisions.
* p< 0.10, ** p< 0.05, *** p < 0.01.

Table 4: The Effects of the Policy Change on Severe Mental Distress (DDD Models)

| **Treatment Effects** | **Severe Mental Distress** | | | **N** | **Sample Mean** |
|---|---|---|---|---|---|
| Full Sample | -0.0331*** | -0.0354*** | -0.0324*** | 70,368 | 0.0809 |
| *Wild Cluster Bootstrap P-Value* | [0.008] | [0.006] | [0.007] | | |
| Fixed effects | x | x | x | | |
| Control variables | | x | x | | |
| State-specific time trends | | | x | | |

The results provides DDD treatment effects obtained from estimating tbe effects of the preexisting conditions provision on the likelihood of experiencing severe mental distress. In addition to using preexisting conditions as the treatment indicator, we further exploit the fact that some states already had high-risk pools in place prior to 2014. All specification use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008), while also implementing a 6-point distribution as introduced Webb (2014) to further account for the small number of clusters. The control variables include age, education, employment status, the number of children living in the household, as well as other ACA provisions. * p< 0.10, ** p< 0.05, *** p < 0.01.



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Table 5: The Effects of the Policy Change on Severe Mental Distress
(Alternative DD Models - Mora & Reggio, 2019)

| **Treatment Effects** | **Severe Mental Distress** | | **N** | **Sample Mean** |
|---|---|---|---|---|
| Full Sample | -0.0145** | -0.0124** | 70,368 | 0.0809 |
| *Wild Cluster Bootstrap P-Value* | [0.040] | [0.048] | [0.007] | |
| States with High-Risk Pools (pre-2014) | -0.0013 | 0.0007 | 49,338 | 0.0784 |
| *Wild Cluster Bootstrap P-Value* | [0.848] | [0.894] | [0.007] | |
| States w/o High-Risk Pools (pre-2014) | -0.0341*** | -0.0334*** | 20,654 | 0.0860 |
| *Wild Cluster Bootstrap P-Value* | [0.001] | [0.001] | [0.007] | |
| Fixed effects | x | x | | |
| Control variables | | x | | |

The results provides DD treatment effects obtained from estimating tbe effects of the preexisting conditions provision on the likelihood of experiencing severe mental distress while using alternative DD specification proposed by Mora and Reggio (2019). All specification use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008), while also implementing a 6-point distribution as introduced Webb (2014) to further account for the small number of clusters. The control variables include age, education, employment status, the number of children living in the household, as well as other ACA provisions. * p< 0.10, ** p< 0.05, *** p < 0.01.

Table 6: The Effects of the Policy Change on Types of on Mental Distress

| | **Sadness** | **Nervous** | **Restless** | **Hopeless** | **Everything an effort** | **Worthless** |
|---|---|---|---|---|---|---|
| Full Sample | -0.0026 | -0.0066 | -0.0030 | -0.0109*** | 0.0171** | -0.0019 |
| *Wild Cluster Bootstrap P-Value* | [0.631] | [0.314] | [0.678] | [0.005] | [0.008] | [0.582] |
| *Sample Mean* | 0.0567 | 0.0865 | 0.1122 | 0.0418 | 0.1453 | 0.0334 |
| Fixed effects | x | x | x | x | x | x |
| Control variables | x | x | x | x | x | x |
| State-specific time trends | x | x | x | x | x | x |

The results provides DD treatment effects obtained from estimating tbe effects of the preexisting conditions provision on the likelihood of experiencing six different emotions, which are included in the K6 measure of mental distress. All specification use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008), while also implementing a 6-point distribution as introduced Webb (2014) to further account for the small number of clusters. The control variables include age, education, employment status, the number of children living in the household, as well as other ACA provisions. * p< 0.10, ** p< 0.05, *** p < 0.01.

Table 7: Effects of the Policy on Mental Distress, by Gender (DD Models)

| | **Male** | | **Female** | |
|---|---|---|---|---|
| | **Severe Mental Distress** | | | |
| Treatment Effect | -0.0016 | -0.0023 | -0.0308*** | -0.0282*** |
| | (0.0051) | (0.0051) | (0.0116) | (0.0112) |
| *Wild Cluster Bootstrap P-Value* | [0.643] | [0.523] | [0.003] | [0.005] |
| Observations | 49,882 | | 18,749 | |
| Fixed effects | x | x | x | x |
| Control variables | x | x | x | x |
| State-specific time trends | | x | | x |

The results provides DD treatment effects obtained from estimating tbe effects of the preexisting conditions provision on the likelihood of experiencing severe mental distress separately by gender. The sample means are 0.0463 and 0.1613 for males and females, respectively. All specification use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008), while also implementing a 6-point distribution as introduced Webb (2014) to further account for the small number of clusters. The control variables include age, education, employment status, the number of children living in the household, as well as other ACA provisions. * p< 0.10, ** p< 0.05, *** p < 0.01.


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Table 8: The Effects of the Policy Change on Health Insurance Coverage (DD Models)

| **Treatment Effects** | **Any Insurance Coverage** | | | **N** | **Sample Mean** |
|---|---|---|---|---|---|
| Full Sample | 0.0054*** | -0.0038*** | 0.0032*** | 6,497,319 | 0.8345 |
| *Wild Cluster Bootstrap P-Value* | [0.000] | [0.000] | [0.000] | | |
| States with High-Risk Pools (pre-2014) | 0.0041*** | 0.0024** | 0.0026** | 4,399,842 | 0.8200 |
| *Wild Cluster Bootstrap P-Value* | [0.003] | [0.020] | [0.017] | | |
| States without High-Risk Pools (pre-2014) | 0.0074*** | 0.0058*** | 0.0044*** | 2,097,477 | 0.8676 |
| *Wild Cluster Bootstrap P-Value* | [0.000] | [0.001] | [0.003] | | |
| Fixed effects | x | x | x | | |
| Control variables | | x | x | | |
| State-specific time trends | | | x | | |

The results provides DD treatment effects obtained from estimating tbe effects of the preexisting conditions provision on the likelihood of having any insurance coverage. All specification use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008), while also implementing a 6-point distribution as introduced Webb (2014) to further account for the small number of clusters. The control variables include age, education, employment status, the number of children living in the household, as well as other ACA provisions.
* p< 0.10, ** p< 0.05, *** p < 0.01.

Table 9: The Effects on Medic Debt and Household Health Expenditures (DD Models)

| | **Have Any Unpaid Medical Bills** | **Total Out-of-Pocket Health Expenditures** | **Health Insurance Expenditures** | **Out-of-Pocket Doctor Expenditures** | **Out-of-Pocket Expenditures on Prescriptions and In-Home Medical Care** | **Out-of-Pocket Expenditures on Hospital Bills and Nursing Homes** | **N** |
|---|---|---|---|---|---|---|---|
| Treatment Effects | -0.0309*** | -143.09 | -57.85 | -76.25 | -30.79 | -56.30 | 70,368 |
| *Wild Cluster Bootstrap P-Value* | [0.001] | [0.277] | [0.389] | [0.294] | [0.173] | [0.335] | |
| *Sample Mean* | 0.1967 | 4,175.19 | 1,564.74 | 1,033.30 | 556.31 | 417.43 | |
| Fixed effects | x | x | x | x | x | x | |
| Control variables | x | x | x | x | x | x | |

The results provides DD treatment effects obtained from estimating tbe effects of the preexisting conditions provision on several outcomes related to health care expenditures. All specification use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008), while also implementing a 6-point distribution as introduced Webb (2014) to further account for the small number of clusters. The control variables include age, education, employment status, the number of children living in the household, as well as other ACA provisions. * p< 0.10, ** p< 0.05, *** p < 0.01.



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Table 10: The Effects of the Policy Change on Physical Health (DD Models)

| | **Fair/Poor Health** | **Excellent/Very Good Health** | **Health Limits Type/Amount of Work** | **Missed Work due to Illness** | **Difficulty Walking** | **N** |
|---|---|---|---|---|---|---|
| Treatment Effects | -0.0915*** | 0.1112*** | -0.0598*** | -0.0359*** | -0.0337*** | 70,368 |
| *Wild Cluster Bootstrap P-Value* | [0.000] | [0.000] | [0.000] | [0.002] | [0.001] | |
| *Sample Mean* | 0.3927 | 0.2618 | 0.3843 | 0.3114 | 0.2377 | |
| Fixed effects | x | x | x | x | x | |
| Control variables | x | x | x | x | x | |

The results provides DD treatment effects obtained from estimating tbe effects of the preexisting conditions provision on several outcomes related to physical health. All specification use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008), while also implementing a 6-point distribution as introduced Webb (2014) to further account for the small number of clusters. The control variables include age, education, employment status, the number of children living in the household, as well as other ACA provisions. * p< 0.10, ** p< 0.05, *** p < 0.01.



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## Appendix

Appendix Table A1: High-Risk Pools Prior to 2014

| High-Risk Pool Prior to 2014 | No High Risk-Pool Prior to 2014 |
|---|---|
| Alabama | Arizona |
| Alaska*** | Delaware |
| Arkansas** | D.C.* |
| California* | Georgia |
| Colorado | Hawaii |
| Connecticut* | Maine |
| Florida | Massachusetts |
| Idaho | Michigan** |
| Illinois | Nevada** |
| Indiana*** | New Jersey* |
| Iowa | New York |
| Kansas | Ohio** |
| Kentucky** | Pennsylvania*** |
| Louisiana*** | Rhode Island |
| Maryland | Vermont |
| Minnesota* | Virginia |
| Mississippi | |
| Missouri | |
| Montana*** | |
| Nebraska | |
| New Hampshire** | |
| New Mexico** | |
| North Carolina | |
| North Dakota** | |
| Oklahoma | |
| Oregon | |
| South Carolina | |
| South Dakota | |
| Tennessee | |
| Texas | |
| Utah | |
| Washington* | |
| Wisconsin | |
| West Virginia** | |
| Wyoming | |

* Early Medicaid expansion (2010-2011); ** Medicaid expansion in 2014; *** Late Medicaid expansion (2015-2016).


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Appendix Table A2: Descriptive Statistics (ACS Sample)

| | **Treatment Group** | **Control Group** |
|---|---|---|
| Age | 52.142 (9.673) | 46.392 (11.099) |
| Male | 0.478 | 0.468 |
| Married | 0.601 | 0.801 |
| Working | 0.337 | 0.769 |
| Unemployed | 0.052 | 0.041 |
| White | 0.778 | 0.804 |
| Black | 0.126 | 0.077 |
| At most 12 years of education | 0.532 | 0.346 |
| >12 years of education | 0.468 | 0.654 |
| Any Insurance Coverage | | |
| *Pre* | 0.834 | 0.847 |
| *Post* | 0.888 | 0.894 |
| N | 741,234 | 5,756,085 |

The table presents descriptive statistics from the ACS sample for both the treatment and the control group.



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Table A3: The Effects of the Policy Change on Severe Mental Distress
(Without State Fixed Effects)

| **Treatment Effects** | **Severe Mental Distress** | | | **N** | **Sample Mean** |
|---|---|---|---|---|---|
| Full Sample | -0.0153*** | -0.0151*** | -0.0149*** | 70,368 | 0.0809 |
| *Wild Cluster Bootstrap P-Value* | [0.008] | [0.008] | [0.009] | | |
| States with High-Risk Pools | -0.0005 | -0.0008 | -0.0008 | 49,338 | 0.0784 |
| (pre-2014) | (0.0063) | (0.0062) | (0.0062) | | |
| *Wild Cluster Bootstrap P-Value* | [0.975] | [0.944] | [0.941] | | |
| States w/o High-Risk Pools | -0.0374*** | -0.0356*** | -0.0361*** | 20,654 | 0.0860 |
| (pre-2014) | (0.0070) | (0.0076) | (0.0076) | | |
| *Wild Cluster Bootstrap P-Value* | [0.000] | [0.001] | [0.001] | | |
| Year fixed effects | x | x | x | | |
| Control variables | | x | x | | |
| State-specific time trends | | | x | | |

The results provides DD treatment effects obtained from estimating tbe effects of the preexisting conditions provision on the likelihood of experiencing severe mental distress. All specification use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008), while also implementing a 6-point distribution as introduced Webb (2014) to further account for the small number of clusters. The control variables include age, education, employment status, the number of children living in the household, as well as other ACA provisions.
* p< 0.10, ** p< 0.05, *** p < 0.01.



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Table A4: The Effects of the Policy Change on Severe Mental Distress
(DD Models with longitudinal sample weights)

| **Treatment Effects** | **Severe Mental Distress** | | | **N** | **Sample Mean** |
|---|---|---|---|---|---|
| Full Sample | -0.0142** | -0.0144*** | -0.0157*** | 70,368 | 0.0809 |
| *Wild Cluster Bootstrap P-Value* | [0.015] | [0.010] | [0.009] | | |
| States with High-Risk Pools (pre-2014) | -0.0005 | -0.0006 | -0.0019 | 49,338 | 0.0784 |
| *Wild Cluster Bootstrap P-Value* | [0.930] | [0.912] | [0.845] | | |
| States without High-Risk Pools (pre-2014) | -0.0334*** | -0.0329*** | -0.0321*** | 20,654 | 0.0860 |
| *Wild Cluster Bootstrap P-Value* | [0.001] | [0.001] | [0.000] | | |
| Fixed effects | x | x | x | | |
| Control variables | | x | x | | |
| State-specific time trends | | | x | | |

The results provides DD treatment effects obtained from estimating tbe effects of the preexisting conditions provision on the likelihood of experiencing severe mental distress. In comparison to the main results, these specifications include longitudinal PSID sample weights. All specification use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008), while also implementing a 6-point distribution as introduced Webb (2014) to further account for the small number of clusters. The control variables include age, education, employment status, the number of children living in the household, as well as other ACA provisions.
* p< 0.10, ** p< 0.05, *** p < 0.01.



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Table A5: The Effects of the Policy Change on Mental Distress
(DD Models with Alternative Cutoffs)

| | | | | | |
|---|---|---|---|---|---|
| **Panel A** | | **K6 - Score >11** | | **N** | **Sample Mean** |
| Treatment Effects | -0.0131** | -0.0129** | -0.0126* | 70,368 | 0.1095 |
| *Wild Cluster Bootstrap P-Value* | [0.045] | [0.046] | [0.051] | | |
| **Panel B** | | **K6 - Score >10** | | | |
| Treatment Effects | -0.0191*** | -0.0204*** | -0.0201*** | 70,368 | 0.1282 |
| *Wild Cluster Bootstrap P-Value* | [0.010] | [0.008] | [0.008] | | |
| **Panel C** | | **K6 - Score >9** | | | |
| Treatment Effects | -0.0173** | -0.0192** | -0.0198** | 70,368 | 0.1596 |
| *Wild Cluster Bootstrap P-Value* | [0.032] | [0.021] | [0.017] | | |
| Fixed effects | x | x | x | | |
| Control variables | | x | x | | |
| State-specific time trends | | | x | | |

The results provides DD treatment effects obtained from estimating tbe effects of the preexisting conditions provision on the likelihood of experiencing mental distress. In these specifications, we use alternative cutoffs for mental distress compared to the main models. All specification use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008), while also implementing a 6-point distribution as introduced Webb (2014) to further account for the small number of clusters. The control variables include age, education, employment status, the number of children living in the household, as well as other ACA provisions. * p< 0.10, ** p< 0.05, *** p < 0.01.

Table A6: The Effects of the Policy Change on Severe Mental Distress
(Less Restrictive Treatment Group Criteria – Condition in at least Two Pre-2014 Waves)

| **Treatment Effects** | **Severe Mental Distress** | | | **N** | **Sample Mean** |
|---|---|---|---|---|---|
| Full Sample | -0.0066** | -0.0060** | -0.0065** | 90,835 | 0.0683 |
| *Wild Cluster Bootstrap P-Value* | [0.036] | [0.044] | [0.039] | | |
| States with High-Risk Pools (pre-2014) | -0.0018 | -0.0005 | -0.0002 | 62,727 | 0.0734 |
| *Wild Cluster Bootstrap P-Value* | [0.763] | [0.912] | [0.982] | | |
| States without High-Risk Pools (pre-2014) | -0.0069* | -0.0061 | -0.0062 | 27,650 | 0.0593 |
| *Wild Cluster Bootstrap P-Value* | [0.085] | [0.117] | [0.114] | | |
| Fixed effects | x | x | x | | |
| Control variables | | x | x | | |
| State-specific time trends | | | x | | |

The results provides DD treatment effects obtained from estimating tbe effects of the preexisting conditions provision on the likelihood of experiencing severe mental distress. In these specifications, we relaxed the assumption that treated individuals need to report that they have had a preexisting condition all four pre-2014 waves. Instead, we use having a condition in at least two pre-2014 waves as the treatment criteria to increase the sample size. All specification use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008), while also implementing a 6-point distribution as introduced Webb (2014) to further account for the small number of clusters. The control variables include age, education, employment status, the number of children living in the household, as well as other ACA provisions. * p< 0.10, ** p< 0.05, *** p < 0.01.

Table A7: The Effects of the Policy Change on Mental Distress
(Excluding and Adding Control Variables)

| **Panel A: Excluding Covariates** | **Including all controls** | **Excluding** | | | **N** |
|---|---|---|---|---|---|
| | | *Employment Status* | *Education* | *Number of Children* | |
| Treatment Effects | -0.0156*** | -0.0161*** | -0.0151*** | -0.0152*** | 70,368 |
| *Wild Cluster Bootstrap P-Value* | [0.006] | [0.005] | [0.007] | [0.006] | |

| **Panel B: Including Additional Covariates** | | | | | **N** |
|---|---|---|---|---|---|
| | *Marital Status* | *Exercise Frequency* | *Smoker* | *Consumed Alcohol in past week* | |
| Treatment Effects | -0.0155*** | -0.0158*** | -0.0156*** | -0.0158*** | 70,368 |
| *Wild Cluster Bootstrap P-Value* | [0.007] | [0.006] | [0.007] | [0.006] | |
| Fixed effects | x | x | x | x | |
| Control variables | x | x | x | x | |
| State-specific time trends | x | x | x | x | |

The results provides DD treatment effects obtained from estimating tbe effects of the preexisting conditions provision on the likelihood of experiencing severe mental distress. The sample means are 0.0809. Compared to the main analysis, we include and exclude additional covariates in these specification to check whether the results are robust to the in- and exclusion of certain control variables. All specification use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008), while also implementing a 6-point distribution as introduced Webb (2014) to further account for the small number of clusters. * p< 0.10, ** p< 0.05, *** p < 0.01.



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Table A8: Falsification Test Using Fair/Poor Health as Treatment Group Indicator
(No Pre-Existing Conditions pre-2014)

| | **Severe Mental Distress** | | | **N** | **Sample Mean** |
|---|---|---|---|---|---|
| Treatment Effects | -0.0064 | -0.0059 | -0.0062 | 61,872 | 0.0606 |
| *Wild Cluster Bootstrap P-Value* | [0.159] | [0.166] | [0.162] | | |
| Fixed effects | x | x | x | | |
| Control variables | | x | x | | |
| State-specific time trends | | | x | | |

The results provides DD treatment effects obtained from estimating tbe effects of the preexisting conditions provision on the likelihood of experiencing severe mental distress. In comparison to the main analysis, we remove individuals with preexisting conditions from the analysis. Instead, our treatment groups consists of individuals with fair or poor health prior to 2014. Individuals with excellent, very good, or good health prior to 2014 served as the control group. Given that treated individuals in this analysis should not have been denied insurance coverage, these specifications serve as falsification tests. Individuals with excellent, very good, or good health prior to 2014 served as the control group. All specification use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008), while also implementing a 6-point distribution as introduced Webb (2014) to further account for the small number of clusters. The control variables include age, education, employment status, the number of children living in the household, as well as other ACA provisions. * p< 0.10, ** p< 0.05, *** p < 0.01.

Table A9: The Effects of the Policy Change on State Migration

| **Treatment Effects** | **Moved to a different state since last survey wave** | | | **N** | **Sample Mean** |
|---|---|---|---|---|---|
| Full Sample | 0.0117*** | 0.0097*** | 0.0104*** | 59,130 | 0.0465 |
| *Wild Cluster Bootstrap P-Value* | [0.003] | [0.007] | [0.006] | | |
| Fixed effects | x | x | x | | |
| Control variables | | x | x | | |
| State-specific time trends | | | x | | |

The results provides DD treatment effects obtained from estimating tbe effects of the preexisting conditions provision on the likelihood of having migrated to a different state since the last survey wave. All specification use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008), while also implementing a 6-point distribution as introduced Webb (2014) to further account for the small number of clusters. The control variables include age, education, employment status, the number of children living in the household, as well as other ACA provisions. * p< 0.10, ** p< 0.05, *** p < 0.01.

Table A10: The Effects of the Policy Change on Medical Debt, by Gender

| **Treatment Effects** | **Have Medical Debt** | | | **N** | **Sample Mean** |
|---|---|---|---|---|---|
| Male | -0.0062 | -0.0057 | -0.0046 | 49,882 | 0.1633 |
| *Wild Cluster Bootstrap P-Value* | [0.525] | [0.566] | [0.760] | | |
| Female | -0.0343*** | -0.0352*** | -0.0310*** | 18,749 | 0.2171 |
| *Wild Cluster Bootstrap P-Value* | [0.000] | [0.000] | [0.002] | | |
| Fixed effects | x | x | x | | |
| Control variables | | x | x | | |
| State-specific time trends | | | x | | |

The results provides DD treatment effects obtained from estimating tbe effects of the preexisting conditions provision on the likelihood of having unpaid medical bills by gender. All specification use the wild cluster bootstrap procedure with 1,000 replications to estimate p-values, as proposed by Cameron et al. (2008), while also implementing a 6-point distribution as introduced Webb (2014) to further account for the small number of clusters. The control variables include age, education, employment status, the number of children living in the household, as well as other ACA provisions.
* p< 0.10, ** p< 0.05, *** p < 0.01.