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The Impact of the ACA Medicaid Expansion on Disability Program Applications

Lucie Schmidt
National Bureau of Economic Research, lschmidt@smith.edu

Lara D. Shore-Sheppard
National Bureau of Economic Research

Tara Watson
National Bureau of Economic Research

THE IMPACT OF THE ACA MEDICAID EXPANSION ON DISABILITY PROGRAM APPLICATIONS

LUCIE SCHMIDT
LARA D. SHORE-SHEPPARD
TARA WATSON

ABSTRACT
The Affordable Care Act (ACA) expanded the availability of public health insurance, decreasing the relative benefit of participating in disability programs but also lowering the cost of exiting the labor market to apply for disability benefits. In this paper, we explore the impact of expanded access to Medicaid through the ACA on applications to the Supplemental Security Income (SSI) and Social Security Disability Insurance (SSDI) programs. Using the fact that the Supreme Court decision of June 2012 made the Medicaid expansion optional for the states, we compare changes in county-level SSI and SSDI caseloads in contiguous county pairs across a state border. We find no significant effects of the Medicaid expansion on applications or awards to either SSI or SSDI, and can reject economically meaningful impacts of Medicaid expansions on applications to disability programs.

KEYWORDS: health insurance, Affordable Care Act, Medicaid, disability benefits, Supplemental Security Income, Social Security Disability Insurance
JEL CLASSIFICATION: H53, I13, I18, I38

I. Introduction

One of the primary goals of the Affordable Care Act (ACA) of 2010 was to expand health insurance coverage and reduce the number of uninsured. Expanded eligibility for Medicaid was to be an important element in achieving this goal, in the process fundamentally changing the nature of Medicaid (Buchmueller, Ham, and Shore-Sheppard 2016). From its inception, Medicaid had been narrowly targeted at only subgroups of the poor: the elderly, those with disabilities, or single parent families who also qualified for cash assistance. By including a provision intended to expand Medicaid to cover *all* individuals with family incomes up to 138 percent of the federal poverty level, the ACA initiated a significant increase in the availability of public insurance beyond those narrowly targeted groups.

Prior to the Medicaid expansion, one path to public health insurance coverage for working-age adults was to participate in one of the two major federal disability benefit

Lucie Schmidt, Lara D. Shore-Sheppard (corresponding author, lshore@williams.edu), and Tara Watson, Department of Economics, Williams College, and NBER.

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programs: Supplemental Security Income (SSI—the federally financed program providing cash assistance to low-income individuals with disabilities) usually comes with Medicaid, and Social Security Disability Insurance (SSDI—the portion of the Social Security program that pays benefits to workers with sufficient work history who have become disabled) allows for access to Medicare after a two-year waiting period. This long-standing link between disability program participation and public health insurance coverage means that changes in the health insurance policy landscape could affect applications to SSI or SSDI.[1] This paper investigates whether the availability of health insurance for adults regardless of disability status affects the decision to apply for disability benefit programs.

Understanding the effects of the ACA Medicaid expansion on disability benefit applications is important. Evidence suggests that roughly 13 to 19 percent of the population have disabilities, and about half of those are in the population ages 18–64 that would be most likely to be affected by the ACA (Brault 2012, 4). In addition, rates of disabling health conditions and disability benefit receipt have grown substantially in recent decades (Autor and Duggan 2003; Case and Deaton 2015). The growth in disability benefit receipt is of particular concern given the sizable public outlays on these programs (approximately $143 billion for SSDI and $55 billion for SSI respectively in 2017; Center on Budget and Policy Priorities 2018; Social Security Administration 2018), and concerns about the possible work disincentives associated with these programs.[2] More generally, understanding the relationship between health insurance provision and disability assistance has implications for cost-benefit analysis of health policy and an understanding of cross-program interactions.

In this paper, we explore the impact of expanded access to Medicaid on applications to disability benefit programs. We rely on the fact that the Supreme Court decision of June 2012 made the ACA Medicaid expansion optional to the states. We exploit three features of the expansion: first, not all states chose to expand health insurance; second, the timing of expansions varied across those states that did choose to expand; and third, some states had more generous income eligibility limits even before expansion.

Although state variation in expansion status and timing would seem to suggest that a difference-in-differences design would be appropriate, this approach requires that non-expanding states offer a good counterfactual for what would have happened to disability program applications in expanding states had they not expanded. However, there are strong geographic patterns in expansion status, with non-expanders tending to be concentrated in the South. In addition, expansion states tend to have lower baseline levels of disability application, as shown in Figure 1, with the lowest SSI application rate in the states that expanded Medicaid prior to 2014. To better identify the causal effect of Medicaid

1 SSI also provides means-tested benefits to individuals over the age of 65. Because the ACA did not affect Medicaid income limits for the elderly and the elderly generally have access to health insurance through Medicare, we would not expect them to be affected by the ACA Medicaid expansion. We focus on working-age individuals throughout this paper, except for the awards data for SSDI which combines county-level awards for working-age adults and their dependents.

2 Eligibility for these programs requires that the applicant show an inability to work, and once on the programs, benefits are reduced as earnings rise. We discuss this in greater detail in Section II.

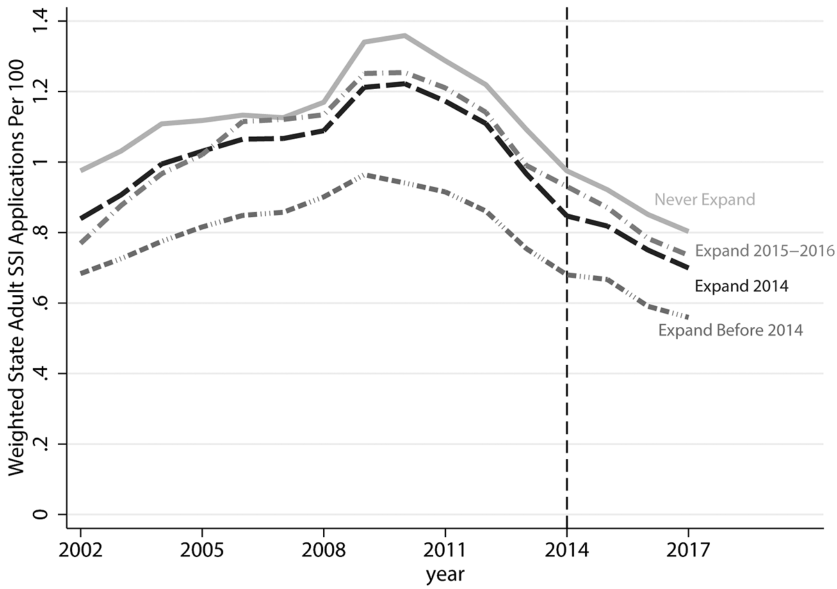

FIGURE 1. State SSI application rates per 100 adults by expansion timing. Values reflect mean state adult SSI applications per 100 adults in the state, weighted by state adult population, for the relevant expansion status group by year. Expansion status is defined by the first time a state exceeds zero for a non-categorical income eligibility limit for Medicaid.

expansion, we take inspiration from the minimum-wage literature and use adjacent counties on either side of a state border to estimate the effect of Medicaid expansions.

In particular, we use county-level data on SSI and SSDI applications obtained from the Social Security Administration to examine contiguous county pairs. Our identification is based on approximately 500 such pairs within which one state took up the Medicaid expansion and the other did not. Relative to a broad comparison of counties in states that expanded and those that did not, counties bordering each other are more likely to share similar labor markets, are more likely to be affected by the same local trends, and are more likely to share macroeconomic shocks. A border county approach that controls for county pair by year fixed effects allows us to focus narrowly on differences arising from the ACA Medicaid expansion choice.[3] Our primary results use a continuous measure of the state Medicaid income eligibility limits, which allows us to exploit additional variation across

3 One concern that might arise with this identification strategy is the possibility that individuals might migrate across county lines in order to obtain Medicaid. However, evidence to date suggests that any such migration is likely to be minimal. Goodman (2017) finds no evidence of a migration response to the ACA Medicaid expansion at the public-use microdata area (PUMA) level, consistent with findings by Schwartz and Sommers (2014) for earlier health insurance expansions. The results suggest that low-income people do not migrate in response to Medicaid eligibility, and the authors can rule out all but very small migration responses.

states and over time in Medicaid income eligibility, although we also show that results are similar if we examine a binary indicator for expansion as is common in the existing literature.

Using data from the Census Bureau's Small Area Health Insurance Estimates at the county level, we first show that the border-county expansion discontinuity strategy finds negative Medicaid expansion effects on uninsurance, with magnitudes similar to those found in the existing literature. We then examine county-level data from the Social Security Administration on applications to SSI and SSDI. We find no significant relationship between the ACA Medicaid expansion and applications to either disability program, and can rule out economically meaningful impacts of 5 percent of baseline levels in either direction. Prior to the implementation of the ACA, some scholars predicted that it would reduce health insurance–motivated disability enrollment (Kennedy and Blodgett 2012), while there was also a possibility that health insurance access would reduce job lock and promote disability program applications. Our results suggest no net impact of the ACA Medicaid expansions on disability program applications or awards.

II. Background

A. SSI AND SSDI

The Social Security Administration oversees two programs for individuals with disabilities. Supplemental Security Income (SSI) is a means-tested program.[4] To receive SSI, an individual must have income and resources below certain standards, but need not have a work history. Social Security Disability Insurance (SSDI) is a disability program that pays benefits to those who are insured; that is, those who have sufficient work history and have paid Social Security taxes.[5]

To participate in either SSI or SSDI, individuals must be determined to have a disability as defined by the Social Security Administration (SSA). The disability determination process is the same for both programs, and includes five steps.[6] In the first step, the individual must demonstrate the inability to engage in "substantial gainful activity"—work that would pay more than a set amount ($1,260 per month in 2020).[7] Next, the severity and

4 SSI covers three groups of individuals: children with disabilities below the age of 18, working-age adults ages 18–64 with disabilities, and individuals 65 and older (no disability required). We limit our SSI focus in this paper to working-age adults with disabilities, since the Medicaid expansion should have had minimal effects on the other two groups given their prior levels of access to health insurance.

5 In general, a worker would need 40 covered quarters of work (20 in the 10 years prior to the disability) to qualify, although younger workers can qualify with fewer covered quarters. There is no means test for SSDI. For example, an applicant could have extensive assets and a spouse with high earnings and could still qualify. SSDI beneficiaries can also include spouses and dependents of the disabled person; these individuals are not reflected in the SSDI applications data but are incorporated in the SSDI awards data.

6 See Lahiri, Vaughan, and Wixon (1995) for a detailed discussion of the disability determination process.

7 The amounts of monthly earnings considered as substantial gainful activity for each year are available on the SSA website: https://www.ssa.gov/oact/cola/sga.html.

expected duration of the disability are considered; the disability must interfere with work-related activities (either physical or mental), and must be expected to last at least 12 months or to end in death. The next step examines whether the disability is on the SSA list of impairments. If it is not, steps 4 and 5 examine whether the individual is capable of performing any of their previous work (step 4) or any work in the national economy (step 5).

Since the process for determining whether an individual meets the medical standard for disability is lengthy, an individual with a disability faces the prospect of a substantial delay between the time of application and the time of disability determination. From application to initial decision takes an average of four months, and only 30 percent of applicants are awarded benefits at this stage. One-third of applicants receive a successful decision on appeal, and appealing to the highest level (the administrative law judge) usually takes two years (Duggan, Kearney, and Rennane 2016). Moreover, for SSDI there is a five-month waiting period after disability onset before payments can begin and an additional 24 months before Medicare can begin. Because a successful application requires showing an inability to work, most applicants will be out of the labor force during this application period. To the extent that they receive their health insurance through their employer, they (and their families) might be without health insurance over this period as well. Once allowed on the programs, individuals must maintain low levels of earnings to retain benefits. For example, earnings for individuals on SSI are taxed away at a 50 percent marginal tax rate. As a result, a number of papers have demonstrated that the disability programs reduce labor supply (for example, Bound, Burkhauser, and Nichols 2003; Von Wachter, Song, and Manchester 2011; Maestas, Mullen, and Strand 2013; French and Song 2014).

Though precise take-up numbers are unavailable, evidence suggests that SSI is incompletely utilized. Among individuals over 65, take-up of SSI has been estimated at around 56 percent (McGarry 1996). It is much more difficult to determine take-up rates of SSI for the working-age population, since, as noted by Currie (2006, 112), "We need to know not only that someone has low income, but also that they are "disabled," a concept that is socially determined and liable to change over time." From contexts where eligibility is more easily determined, we know take-up of safety net programs is far from complete (Currie 2006). Partly because of the costs of applying for SSI/SSDI, a number of papers have shown that changes in the relative costs and benefits of other programs affect disability benefit application and receipt (Bound, Kossoudji, and Ricart-Moes 1998; Garrett and Glied 2000; Schmidt and Sevak 2004; Goodman-Bacon and Schmidt 2020).

B. LINKS BETWEEN SSI, SSDI, AND PUBLIC HEALTH INSURANCE

From the time of its enactment until the ACA, Medicaid has generally had a categorical requirement—that is, only individuals who are members of an eligible category could receive coverage. These categories include children and their parents, and the elderly, blind, and those with disabilities, with each category having its own set of income limits. The Medicaid income limits for individuals with disabilities are generally the SSI income limits (typically around 75 percent of the poverty line), with some exceptions, and are therefore below the ACA's non-categorical income eligibility limit of 138 percent of the federal poverty line. Prior to the ACA, some states did obtain permission to extend coverage to limited groups of childless adults regardless of disability status under a waiver of the federal categorical eligibility rules. In all but two states (DC and Vermont), the income eligibility limit to obtain a full Medicaid benefits package for childless adults was below the ACA's income eligibility limit.[8]

Before the ACA Medicaid expansion, receipt of SSI or SSDI provided the clearest path to public health insurance for individuals with disabilities. In the majority of states, SSI recipients automatically receive Medicaid with no separate application. A set of seven states have the same eligibility criteria for SSI and Medicaid but require an additional Medicaid application (Alaska, Idaho, Kansas, Nebraska, Nevada, Oregon, and Utah). In an additional nine states, Medicaid eligibility criteria can be more restrictive than those for SSI (Connecticut, Hawaii, Illinois, Minnesota, Missouri, New Hampshire, North Dakota, Oklahoma, Virginia; Social Security Administration 2017). Some states offer Medicaid coverage to individuals with disabilities who have incomes above the SSI income limit but below the poverty line (Watts, Cornachione, and Musumeci 2016); individuals applying for this Medicaid coverage would need to go through the disability determination process even if they were not income-eligible for SSI. SSDI recipients receive health insurance through Medicare, although there is a two-year waiting period before they are eligible.

In the absence of a robust unconditional public health insurance program, applying for disability benefits may require going without health insurance for a period of months or years. The restriction on gainful activity means that individuals with disabilities potentially eligible for SSI or SSDI are unlikely to obtain health insurance through their employer, the most common source of health insurance for nonelderly adults in the United States. In the case of SSI, it is also unlikely that the recipient would have health insurance through a spouse's employer, as most jobs offering health insurance would pay a salary that exceeds the very low household income limits for SSI.

There are several pathways through which the changes in health insurance access provided by the ACA Medicaid expansion may affect SSI and SSDI applications. First, the Medicaid expansion represents an alternative means of obtaining health insurance that does not require application for or participation in a disability program. As noted above, the application process for SSI and SSDI is both lengthy and uncertain, and applicants would have to give up their jobs and perhaps their employer-sponsored insurance to apply. While benefits for a successful applicant are paid based on application date rather than approval date, a potential applicant who lacks savings and is credit-constrained may face severe barriers to applying. With Medicaid eligibility expanded to all low-income adults regardless of disability status, individuals with disabilities have the option to immediately enroll in Medicaid without going through the onerous process of applying for cash SSI or SSDI benefits.[9] We refer to this as the "alternative source of health insurance" channel.

8 We account for this waiver coverage in our empirical work. In all but a few states, the ACA's Medicaid income eligibility limit was higher than the income limit for parents as well.

9 As noted in an issue brief from the Kaiser Family Foundation, "In states that implement the ACA's Medicaid expansion, more people with disabilities may qualify for Medicaid based solely on their low income status, which enables them to enroll in coverage as quickly as possible, without waiting for a disability determination" (Musumeci 2014, 1).

If this channel is important, it would suggest that Medicaid expansions could reduce applications to disability programs.

Second, as Maestas, Mullen, and Strand (2014) point out, without public health insurance, some individuals with disabilities do not apply for disability benefits because they would lack health insurance coverage throughout the lengthy application process. The expansion of Medicaid access through the ACA may allow them to quit their jobs to apply for disability benefits, reducing health-insurance-related "employment lock." In addition, disability program participation leads to health insurance coverage only for the individual with the disability. The Medicaid expansion could allow multiple members of a family to have insurance coverage through Medicaid even if the former primary earner gave up their job to apply for SSI or SSDI. This "employment lock" pathway would tend to increase disability applications.

Third, expanded access to Medicaid may make individuals more aware of the possibility of eligibility for additional public programs. Specifically, as individuals apply for Medicaid, they may be directed by state offices to apply for disability benefits if they are considered to be eligible.[10] This "information channel" would tend to increase applications to disability programs.

Finally, by improving access to health insurance, Medicaid may give individuals additional resources to diagnose and document health conditions, ultimately leading to higher rates of disability program applications, and possibly higher success rates for existing applications. It is also possible that access to health insurance could improve health, leading to lower rates of disability in the future and thus lower applications. These health- and diagnosis-related channels are unlikely to be evident in the early years of the Medicaid expansion, however, and we do not expect to see evidence of them in the time period we study.

In sum, the various pathways by which Medicaid expansion could affect disability program applications go in both directions. With the research design in this paper it will not be possible to distinguish the relative magnitude of the different pathways; we will only be able to see the sign and magnitude of any net effect. We expect estimated effects to be smaller for SSDI than for SSI because SSI is means-tested and more likely to be taken up by individuals under 138 percent of the poverty line, the non-categorical Medicaid income threshold in most expansion states. SSDI has a work history requirement, implying that potential SSDI recipients have relatively higher incomes, so the Medicaid expansion may be relatively less important for this group.

Our focus in this paper is on applications to disability programs, since that is the initial margin upon which Medicaid expansion may have an impact. To provide further information about the relative disability status of applicants and to understand the implications for the disability programs, we also examine new awards of disability benefits. If applicants who are marginal—in the sense that their decision to apply is changed by the expansion

10 Musumeci (2014, 10) notes that "the online version of the . . . application contains two questions designed to identify people with disabilities."

of Medicaid—have less severe impairments, then a change in applications may not translate into a change in awards.

The Medicaid expansion also has potential implications for disability program caseloads through its impact on awards (and perhaps impacts on exits). However, there are serious limitations to the empirical investigation of disability caseloads per se because they are a stock that evolves slowly. Disability programs usually have very low exit rates (Raut 2017; Social Security Administration 2004; Duggan, Kearney, and Rennane 2016), and as a result, the stocks do not respond as quickly to external policy changes as flows do. In addition, caseloads reflect policy and economic changes in previous periods, so it is unclear how long it would take for any Medicaid expansion impacts to become apparent in caseloads.

In the context of welfare caseloads following the 1996 welfare reform, Klerman and Haider (2004) show that a static model of stocks is likely to be misspecified. A static stock model suffers from omitted variables bias; in particular, such a model omits necessary lags of the explanatory variables and interactions between the lags. Their intuition for this finding is that since the stock depends on previous economic conditions and policies, even under the extremely restrictive assumption of no duration dependence, information about previous conditions is necessary to explain caseload sizes. This concern about caseloads is particularly worrisome for disability programs, which by design have long spells of participation. Thus, to understand the impacts of ACA Medicaid expansions, we focus on applications and awards rather than on caseloads.

III. Previous Literature

Though not our primary focus, we begin by investigating the effect of Medicaid expansions on insurance status. Prior researchers have shown that the Medicaid expansion is associated with increases in health insurance coverage among populations targeted by the policy. While Courtemanche et al. (2017) do not see a significant effect of Medicaid expansion using a standard state differences-in-differences approach for working-age adults in years 2011 to 2014, they estimate a statistically significant 3.1 percentage point increase in insurance due to the Medicaid expansion when using local areas with previously higher or lower uninsurance rates in a triple-differences specification. They conclude that the naïve differences-in-differences specification understates the true effect of the policy. Similarly, Kaestner et al. (2017) find a significant reduction in uninsurance of 2.7 percentage points for parents with a high school education or less and 3.4 percentage points for childless adults with a high school education or less using a differences-in-differences design in data from 2010 to 2014. Leung and Mas (2018) find a 1.6 percentage point effect on the probability of being insured in a differences-in-differences analysis of childless adults and a 7.9 percentage point effect for childless adults under the poverty line. Buchmueller, Levy, and Valletta (2019) find that the Medicaid expansion was associated with an 8 percentage point decrease in uninsurance for unemployed workers, but had no effect on the coverage of employed workers. These studies and others suggest that basic differences-in-differences analyses show a modest effect of ACA Medicaid expansions on uninsurance overall, and analyses that narrow in on target populations of interest show an effect in the 1 to 8 percentage point range.

There is a small but growing literature on the relationship between public health insurance and applications to disability programs. Maestas, Mullen, and Strand (2014) examine county-level disability program applications in Massachusetts following the health insurance reform in 2006, comparing the change in county-level disability program applications in Massachusetts relative to the change in a group of counties in comparison states. They find modest increases in disability applications (1–3 percent) in Massachusetts relative to neighboring states in the first year after reform, and no difference after the first year. Also focusing on a state-level program but using a different identification strategy, Baicker et al. (2014, 327n8) study a randomized lottery offering Medicaid to some residents of Oregon. Although disability program applications are not their main focus, they report some findings on applications in a footnote, characterizing their findings as "suggestive evidence of statistical effect on SSDI and SSI applications, but not one that was economically meaningful (e.g., Medicaid coverage may cause about a 1 percentage point increase in applications to each program, and perhaps a half a percentage point increase in approvals for SSDI)."

Anand et al. (2019) is the work most similar to ours, examining the response to the ACA Medicaid expansion using quarterly administrative data from the Social Security Administration on application rates by Public Use Microdata Area (PUMA). The authors carefully match PUMAs based on pre-2014 characteristics, keeping only those PUMAs in expansion and non-expansion states (where expansion is defined as of January 2014) that match closely with at least one other PUMA. However, they use these expansion and non-expansion PUMAs in their matched sample in a standard difference-in-differences regression of the application rate by PUMA and quarter, thus comparing all matched expansion PUMAs to all matched non-expansion PUMAs rather than narrowly comparing outcomes within matched pairs. They find that SSI applications were slightly higher in PUMAs in states that expanded in the first quarter of 2014 than in non-expansion PUMAs between one and five quarters after the expansion. There is some evidence of dissimilar pre-expansion trends in the expansion and non-expansion groups, however, raising the question of whether the effect they find is due to the expansion or differential underlying trends related to recession recovery.

Two other papers, Burns and Dague (2017) and Soni et al. (2017), focus exclusively on stock measures such as participation and caseloads. Burns and Dague (2017) investigate Medicaid expansions to childless adults that occurred between 2001 and 2013, prior to most ACA-related expansions. The authors use individual data from the American Community Survey, comparing states with coverage for childless adults to states without coverage and also estimating similar specifications comparing differences in income eligibility limits for childless adults across states. They find that when a state covers childless adults under Medicaid, SSI participation is lower by 0.17 percentage points, a 7 percent relative decrease. Soni et al. (2017) use a state difference-in-differences approach to examine the ACA Medicaid expansion, comparing SSI participation in states that expanded Medicaid as of 2015 with participation in states that did not expand Medicaid or did not expand until after 2015. They report results suggesting that the number of SSI recipients in a state fell by about 3,500 per year in expansion states relative to non-expansion states (a 3.3 percent change in participation) after 2014.[11] In sum, the existing literature tends to find economically small but mixed effects of Medicaid eligibility expansion on disability applications, with most statistically significant estimated impacts on applications being small and positive and estimated participation and caseload effects tending to be negative or near zero.[12]

Our work contributes to the existing literature on the impact of expanded Medicaid eligibility on disability program participation in several important ways. First, we focus on applications and awards, which as discussed above are the key margins upon which Medicaid expansion may have an impact and are not susceptible to the estimation problems faced by static models of caseload stocks. Second, we examine the most significant change in access to Medicaid since its inception using a new identification strategy (differences in adjacent county pairs that differ in their Medicaid expansion status) that, compared with a state differences model, more plausibly delivers an unbiased estimate. Third, we allow for a rich specification of Medicaid eligibility, treating the Medicaid expansion not just as something that turns "on" or not at a given time, but allowing for the possibility of differential effects based on the levels of Medicaid income eligibility limits prior to the ACA expansion.

IV. Empirical Approach

To identify the impact of expanded access to Medicaid via the ACA on SSI and SSDI applications and awards, we use variation in non-categorical Medicaid eligibility (that is, Medicaid eligibility that does not require the individual to establish the presence of a disability or a dependent child) resulting from the June 2012 Supreme Court decision making the Medicaid expansion optional to the states. Like other studies of the ACA, we take advantage of variation by state and over time in the Medicaid expansion. A key empirical challenge is that there is nonrandomness, including a strong geographic correlation in which states chose to expand, and the outcomes of interest may be trending differently in different parts of the country. For example, trends in disability status are different in southern states than from states outside the South, and the fact that many of the non-expansion states are in the South could lead to spurious correlation between expansion

11 The Soni et al. (2017) results appear to be sensitive to specification. In particular, we find that specifications using similar data and method but caseload *rates* (recipients per population) instead of numbers of recipients show no impact of the expansion. Also, their participation results appear sensitive to the inclusion of lagged unemployment rates, as Klerman and Haider's (2004) results would suggest (results available from the authors).

12 Chatterji and Li (2017) use a synthetic control approach to examine the impact of transitions of state or local public insurance programs to Medicaid under the ACA that took place in three states (Connecticut, Minnesota, and California) and the District of Columbia between 2010 and 2013 on the percentage of state nonelderly population receiving SSI. Chatterji and Li examine each state separately and find an effect that is statistically distinguishable from zero only in Connecticut: a marginally statistically significant 0.11 percentage point reduction in SSI receipt. They also report trying to examine SSI application rates but being unable to form suitable synthetic controls for application rates for those four states.

status and applications to disability programs. To address this challenge, we conduct our analysis at the county level and compare disability benefit applications within contiguous county pairs, in which one county in the pair is in a state with a given Medicaid income eligibility limit and the adjacent county is in a state with a different limit.

The county border approach has been used effectively to study the employment effects of state minimum wages (see Dube, Lester, and Reich 2010, 2016). Counties bordering each other are more likely to share similar labor markets, are likely to be affected by the same local trends, and are more likely to share macroeconomic shocks than are counties that do not share a common border (Allegretto et al. 2013; Dube, Lester, and Reich 2016). This research design allows us to focus narrowly on differences arising from the ACA Medicaid expansion choice by comparing changes over time in outcomes from US counties on either side of a state border. In this approach, the identifying assumption is that the change in the outcome of interest in the county in the non-expanding state is a reasonable counterfactual estimate for how the outcome of interest would have changed in its neighboring county across the border if the Medicaid expansion had not occurred.

A simple illustration of the nature of our research design can be seen in Figure 2, where the substate divisions shown are counties, and contiguous border county pairs are shown in gray. County pairs that differed in their Medicaid expansion status as of April 2014 are highlighted in dark gray. At that time, there were 488 discordant county pairs (where one county was in a state that had expanded Medicaid and the neighboring county was in a state that did not) out of a total of 1,197 county pairs. In addition, we take advantage of two sources of variation not visible in Figure 2. First, states had different income eligibility limits for Medicaid prior to the ACA expansion, which means that the ACA expansion represented a more substantial increase in access to public insurance in some states than in others. Second, the timing of Medicaid expansion was not uniform, with some states choosing to expand earlier or in a gradual way, and others choosing to expand later.[13] Some states began to expand starting in 2010, and while 21 states officially adopted the ACA Medicaid expansion on January 1, 2014, other states did not expand until later in 2014 or subsequent years. We incorporate expansions through 2016 in most specifications. We also exploit variation at the county level in expansion timing in California, which was the only state to roll out its early Medicaid expansion on a county-by-county basis. Online Appendix Table 1 shows all states with border-pairs providing variation in our sample based on differences in the non-categorical income eligibility limit.

States typically have three Medicaid income limits applying to working-age adults. The non-categorical limit applies to all adults regardless of family structure or disability status. As of 2010, only eight states (including DC) had a nonzero, non-categorical limit; in seven of these states eligibility ranged from 73 to 110 percent of the poverty line, and DC had a limit of 211 percent. All states had categorical eligibility for parents and individuals with disabilities in 2010, with limits ranging from 17 to 215 percent of the poverty line for

13 The number of county pairs that are discordant using this method is considerably higher, varying by year from a high of 913 discordant county pairs in 2010 to 768 in 2015.

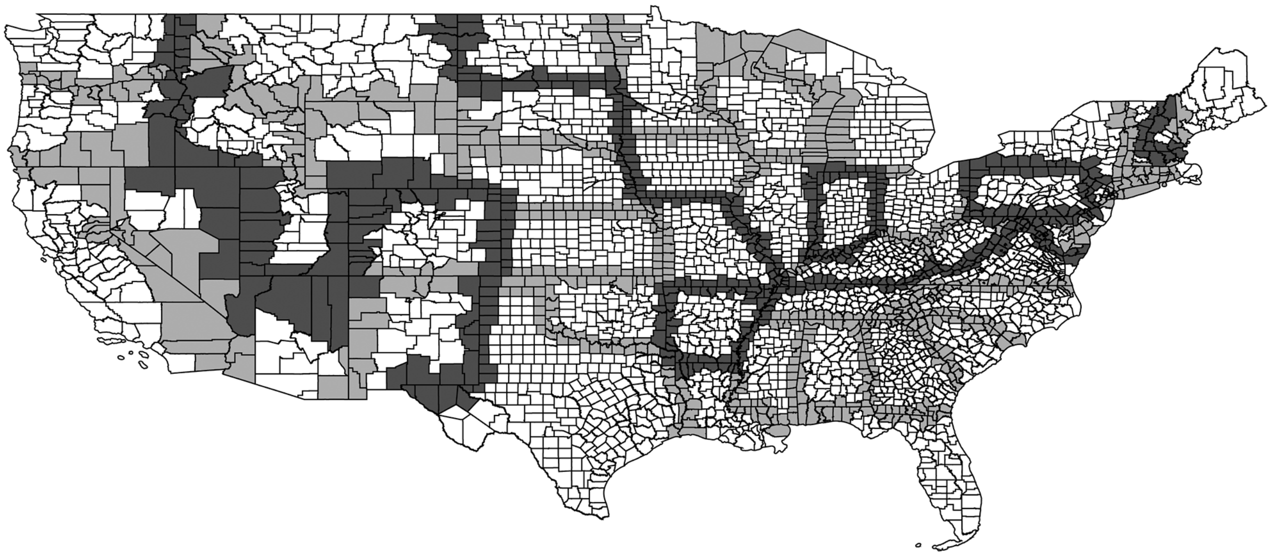

FIGURE 2. Contiguous border county pairs in the US with a Medicaid expansion differential, April 2014. State border counties in gray; dark gray shading indicates that non-categorical limit differs from non-categorical limit of bordering county.
Sources: Heberlein et al. (2013); Brooks et al. (2015); Rudowitz, Artiga, and Arguello (2013); and the Kaiser Family Foundation website "Status of State Action on the Medicaid Expansion Decision" (http://www.kff.org/health-reform/state-indicator/state-activity-around-expanding-medicaid-under-the-affordable-care-act/).

parents and 65 to 150 percent of the poverty line for individuals with disabilities.[14] In states that adopted the ACA Medicaid expansions, the non-categorical limit was set to a minimum of 138 percent of poverty (almost always set exactly at 138 percent), effectively setting 138 percent as a floor for parents and those with disabilities as well.

Because a disability benefit determination would be necessary before the disability limit would apply, the relevant Medicaid limit for individuals making a decision about the value of disability benefits or facing “employment lock” is the parent or non-categorical income limit.[15] We cannot distinguish between parents and nonparents in the applications data, and because a majority of adults do not have dependent children at a given point in time (especially older working-age adults who are more likely to have a disability), the non-categorical income limit is most relevant.

We consider the following difference-in-differences specification estimated on a sample of all counties in the continental United States for the period 2010–16:

$$y_{ct} = \beta MedicaidLimit_{s(c)t} + X_{ct}\Gamma + \phi_c + \tau_t + \varepsilon_{ct} \qquad (1),$$

where y_{ct} denotes the various outcomes of interest (described in detail in Section V below) for county c in time t, where t denotes year. The variable $MedicaidLimit_{s(c)t}$, which is typically set at the state level (and thus denoted by $s(c)$), is the Medicaid non-categorical income limit, that is, the baseline income limit that applies to adults regardless of whether they have children or disabilities. It is measured as a percentage of the federal poverty line. The vector X_{ct} includes time-varying controls such as demographic characteristics, and φ_{c} and τ_{t} are county and time fixed effects, included to account for unmeasured heterogeneity in outcomes across space and time that may be correlated with expansion status.[16] This equation corresponds to the approach commonly used in the ACA Medicaid expansion literature thus far, although it has typically been estimated at the state level or individual level with state and year fixed effects rather than at the county level. The identifying assumption implicit in this approach is that after accounting for county-specific and time-specific fixed effects, outcomes in counties with different levels of non-categorical Medicaid income limits would be changing in the same way over time if the expansion had not occurred. We estimate this model using our county-level data, clustering our standard errors at the state level to account for the fact that the variation in expansion status is at the state level.

The county border discontinuity approach requires limiting the data to border counties and restructuring the data so that each county is observed once per year per adjacent

14 Prior to the ACA, there were two eligibility pathways to Medicaid for individuals with disabilities: SSI-related eligibility and poverty-related eligibility. In most states, SSI-related eligibility includes all individuals eligible for federal SSI payments or for the optional state supplements. The income cutoffs for SSI recipients were typically below the poverty line, and in some states individuals with disabilities could access Medicaid with higher incomes under the poverty-related pathway.

15 The results are robust to an alternate measure of the income limit that is the maximum of the non-categorical limit and the limit for individuals with disabilities.

16 We also examine the robustness of our results to the inclusion of controls for county unemployment rates, but this does not substantively change our estimates (see Online Appendix Tables 4 and 5).

pair. This restructuring is necessary so that observations can be assigned a vector of county pair–year fixed effects that allow the adjacent border county to serve as a counterfactual. A county that is part of more than one county pair could be observed multiple times, and the regressions are reweighted so that the final weight of the county is proportional to population.[17] Standard errors are adjusted accordingly.[18]

Using the restructured data, we estimate a modified version of equation 1:

$$y_{cpt} = \beta MedicaidLimit_{s(c)t} + X_{ct}\Gamma + \phi_c + \tau_{pt} + \varepsilon_{cpt} \qquad (2),$$

where the subscript p denotes a county pair and τ_{pt} is a pair-specific time effect instead of a national time effect. The use of the pair-specific time effect means that we are using only variation in expansion status within each contiguous border county pair. The identifying assumption is thus that a difference in expansion status within a contiguous border county pair is uncorrelated with pair-specific unobservables, that is, within a pair the outcome in the county with the expansion would have changed in the same way as in the nonexpansion county if the expansion had not occurred. Our border-pair sample includes all contiguous county pairs in all years for which data are not missing, regardless of whether they are discordant with respect to Medicaid income eligibility limits. However, only those pairs that experience a differential change in expansion status within the pair during the years of our sample contribute to the identification because the county dummies absorb initial within-pair differences and county pair by year fixed effects absorb common changes. To determine the impact of restricting our estimation sample to border counties, we estimate the model of equation 1 on the subsample of counties used in the estimates of equation 2 and examine the changes both in parameter estimates and in confidence intervals as we change samples and estimation strategies.

V. Data

We combine data from a number of different sources for the analysis. Our primary outcomes of interest are applications and awards for SSI and SSDI, which were constructed for us at the county level by the Social Security Administration.[19] We use data on SSI applications and awards for the working-age population 18–64, since the Medicaid expansion

17 For example, if a county is in three distinct border-pairs, the weight for each observation corresponds to one-third of its population, so in aggregate the weight of the county corresponds to its population. As a robustness check we also estimate our models without weighting and find similar results (see Online Appendix Tables 4 and 5).

18 Standard errors are clustered at the state level throughout. The finite sample degrees of freedom correction used in the Stata clustering is incorrect in this setting because county-years are included more than once. We correct for this by including a set of constants in the regression equation corresponding to dummy variables for the county × county pair. These are collinear with the other fixed effects in the model so do not change the coefficients, but generate an approximate correction for the degrees of freedom. We thank Michael L. Anderson for suggesting this solution.

19 SSDI applications and awards by county were estimated using the most recently updated Title II Disability Research Files, while the same measures for SSI are estimates from the most recently updated

was likely to have much smaller effects on children and on the elderly. For SSDI, we use applications data for ages 18–64, but the awards data set also includes spouses and dependents of applicants. We use data from 2010 to 2016 for applications to determine the effect of the current Medicaid non-categorical limit. Given that there is likely to be a delay in awards relative to applications, we use data from 2011 through 2017 to analyze awards, and allow both the current and lagged Medicaid limits to have an effect. We denominate these county aggregates by estimates of the prime-age (20–64) population from the Census Bureau, except in the case of all-age SSDI awards which is denominated by total population. Our data set reports counties with zero applications or awards, but applications and awards between one and nine are coded as missing for confidentiality purposes.[20] We recode all such counties as having five applications or awards.

In addition to disability program applications and awards, we examine health insurance coverage at the county level as an outcome. Though other researchers have documented an effect of ACA expansions on uninsurance, it is important to assess whether a similar effect is observed using aggregate county-level data, using our sample of counties and years, and using our preferred border-pair design. Health insurance coverage data at the county level are only available from the Census Bureau's Small Area Health Insurance Estimates (SAHIE) program, which produces estimates of the fraction with and without health insurance coverage by age, sex, and income group at the county level.[21] The SAHIE estimates are model-based, incorporating information from the American Community Survey, federal tax return data, data on Supplemental Nutrition Assistance Program caseloads, Medicaid and Children's Health Insurance Program caseloads, census population estimates, County Business Patterns, and the 2010 census.

We determine the non-categorical Medicaid income eligibility limits from a variety of sources. The primary sources for Medicaid income eligibility levels are reports published by the Kaiser Family Foundation (Cohen Ross et al. 2009; Heberlein et al. 2013; Heberlein et al. 2011, 2012; Brooks et al. 2015; Brooks et al. 2016; Rudowitz, Artiga, and Arguello 2013) and the Urban Institute's TRIM3 program rules database (Urban Institute, n.d.) supplemented by information from state plan amendments available from the Centers for Medicare and Medicaid Services and state websites.[22]

The county-level control variables include the share of the county-level population that is non-Hispanic black, the share that is Hispanic, and the share ages 50–64 from annual Census Bureau estimates. In robustness tests, we control for the unemployment rate, which we obtained from the Bureau of Labor Statistics Local Area Unemployment series, but we do not include it in our main specifications because of potential endogeneity. We determine which counties are contiguous using the 2015 Census Bureau county adjacency

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Title XVI Disability Research Files. Applications and awards are for the calendar year, reported in June of the following year.

20 The SSDI awards data set, unlike the other three data sets from SSA, reports any number below 10 as missing, and these observations are excluded from the analysis.

21 While we would also like to examine Medicaid coverage rates, unfortunately such data do not exist at the county level.

22 Our compilation of these non-categorical limits is available from the authors by request.

TABLE 1. Summary statistics: Weighted means by sample and by year

Variable	All counties sample 2010	Contiguous counties sample 2010	All counties sample 2016	Contiguous counties sample 2016
SSI working-age applications per 100 working-age adults	1.236	1.301	0.580	0.968
SSDI working-age applications per 100 working-age adults	1.453	1.520	0.985	1.049
SSI working-age awards per 100 working-age adults	0.344	0.364	0.187	0.201
SSDI all-ages awards per 100 population	0.322	0.346	0.227	0.248
Uninsured per 100 population	17.685	16.041	9.965	8.948
Low-income uninsured per 100 low-income population	28.257	26.248	15.960	14.630
Medicaid non-categorical income limit > 0	0.125	0.175	0.618	0.708
Medicaid non-categorical income limit (fraction relative to FPL)	0.128	0.188	0.902	1.025
Percentage non-Hispanic black	13.281	14.114	13.616	14.509
Percentage Hispanic	16.455	12.171	18.002	13.690
Percentage population ages 50–64	19.088	19.568	19.550	20.064
Unemployment rate	9.729	9.614	4.938	5.036
Observations	3,088	2,394	3,088	2,394
Unique counties	3,088	1,140	3,088	1,140

Note: Application and awards data are based on administrative counts. SSDI applications data and SSI data based on applications/awards for ages 18–64; SSDI awards are based on all-age data. If the state does not have expanded non-categorical income eligibility for Medicaid, we code that as an income eligibility limit of zero. "Observations" refers to the number of observations in the SSI applications data. Weights are working-age population in the county.

file, which lists all adjacent counties. We adjust the county pair list to keep only counties that share a common land border or that are separated by a body of water but connected by a bridge or boat using information from a 1991 Census Bureau file that lists the type of adjacency (common land border, touch at a corner, touch across body of water, etc.).[23]

Table 1 presents summary statistics for 2010 and 2016, broken out by sample (all counties versus contiguous counties). Both SSI applications and awards decline significantly during

23 We do not consider counties as pairs if they meet at a corner only or they are separated by a body of water and have no direct bridge or boat connection (for example, counties that "touch" across the Great Lakes). We also merge incorporated cities in Virginia that are entirely contained within another county into that county.

our sample time period as the economy recovers from the Great Recession. The two samples are very similar in their unemployment rates, but the contiguous counties sample has fewer Hispanic residents on average and more residents in the 50 to 64 age range. We control for race/ethnicity and age composition of the population in the regressions.

VI. Results

A. DESCRIPTIVE ANALYSIS

While the county border discontinuity approach has strong intuitive appeal since it narrows the comparison to an arguably more similar counterfactual, it is important to evaluate it against the typical difference-in-differences approach that is common in the literature. While it is not possible to test the models against each other explicitly, since each involves a different identifying assumption, various methods of examining the validity of these models have been suggested in the literature (see Dube, Lester, and Reich 2010, 2016; Allegretto et al. 2013; and Neumark, Salas, and Wascher 2014).

In Table 2, we show that for the sample of border counties in 2010, the initial levels of key variables are more similar in adjacent counties than in the full sample of counties outside the state. The mean absolute differences in values of SSI and SSDI applications and awards, as well as our covariates, are smaller for contiguous pairs in data from 2010 (before the ACA generally became effective) than they are for pairs formed by matching every other county from outside the state with each border county in the data. The *p*-value of the difference is under 1 percent for all variables except the 2010 non-categorical Medicaid income limit (which is to be expected because a majority of states had a limit of zero at that time). From Table 2 it is clear that baseline observable characteristics are more similar in contiguous counties.

As a second set of descriptive analyses, we graphically explore year-by-year effects of being in expansion versus non-expansion counties, where expansion is defined as having any non-categorical income limit above zero by 2016. The estimates are generated using three different specifications. For the first, we interact an "ever expand" dummy with year dummies, controlling for demographic variables, county fixed effects, year fixed effects, and leaving 2010 as a reference year. The coefficients therefore reflect mean differences between counties in expansion states and non-expansion states relative to the difference in 2010 and allow us to see trends in the evolution of two groups of counties. We call this the "All County DD" specification and it is described by equation 3:

$$y_{ct} = \sum_{t=11}^{16} \beta_t (EverExpand_{s(c)} {}^* \tau_t) + X_{ct}\Gamma + \phi_c + \tau_t + \varepsilon_{ct} \quad (3).$$

The coefficients β_t allow us to see year-to-year variation between 2011 and 2016 in expansion counties relative to adjacent counties, with 2010 serving as the baseline.

We also run the same analysis described in equation 3 using the contiguous county sample, which we refer to as the "Contig County DD." Finally, we control for county border-pair by year dummies for the "Border-Pair" specification, described by the following:

TABLE 2. Mean absolute deviation (MAD) of baseline variables in 2010, absolute difference between sample border counties and controls

	Control group is all counties outside state	Control group is adjacent border county	*p*-value of difference
MAD of SSI applications per 100	0.8921	0.5500	<0.001[a]
	(0.0515)	(0.0313)	
MAD of SSI awards per 100	0.2478	0.1689	<0.001[a]
	(0.0103)	(0.0084)	
MAD of SSDI applications per 100	0.8784	0.5445	<0.001[a]
	(0.0462)	(0.0319)	
MAD of SSDI awards per 100	0.1737	0.1168	<0.001[a]
	(0.0090)	(0.0071)	
MAD of unemployment rate	3.4709	1.8799	<0.001[a]
	(0.1047)	(0.1083)	
MAD of poverty rate	6.8208	4.2804	<0.001[a]
	(0.2163)	(0.2192)	
MAD of percentage non-Hispanic black	12.7283	4.9747	<0.001[a]
	(1.0830)	(0.7365)	
MAD of percentage Hispanic	9.6108	4.1770	<0.001[a]
	(0.7777)	(0.6053)	
MAD of percentage ages 50–64	2.9025	2.1990	<0.001[a]
	(0.0953)	(0.1472)	
MAD of non-categorical income limit relative to the poverty line	0.1208	0.0926	0.051[c]
	(0.0354)	(0.0371)	

Note: Cells reflect unweighted mean absolute difference between value of the variable in 2010 in a border county in the contiguous county sample and all counties in the relevant control group. The final column reflects the difference between the two means estimated using seemingly unrelated regression. Robust standard errors clustered on state in parentheses. $^{a}p < 0.01$, $^{b}p < 0.05$, $^{c}p < 0.10$.

$$y_{cpt} = \sum_{t=11}^{16} \beta_t \left(EverExpand_{s(c)}{}^{*}\tau_t \right) + X_{ct}\Gamma + \phi_c + \tau_{pt} + \varepsilon_{ct} \qquad (4).$$

Analyses are weighted by prime-age county population and standard errors are clustered at the state level.

Figure 3 shows the results of these three analyses with the non-categorical Medicaid income limit as the dependent variable—that is, Figure 3 illustrates the timing of the policy change. A handful of states expanded non-categorical eligibility for Medicaid between

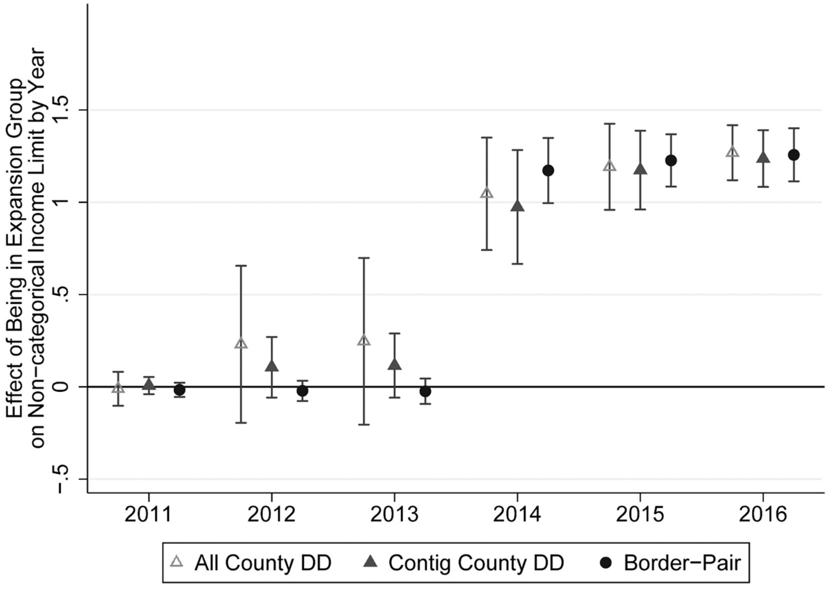

FIGURE 3. Year-by-year effects of being in expansion group on non-categorical income limit. Non-categorical income limit is income eligibility limit relative to the poverty line. Expansion group status is defined as having any non-categorical income limit greater than zero by 2016. All models include county fixed effects and year fixed effects, with base year 2010. A dummy variable for whether the county is in the expansion group is interacted with each year 2011 through 2016, so the coefficients shown indicate the difference between the expansion group and the non-expansion group relative to the baseline 2010 difference between the expansion group and non-expansion group. Additional controls include fraction non-Hispanic black, fraction Hispanic, and percentage aged 50 to 64. "All County DD" reflects the baseline model on the full sample. "Contig County" reflects the same baseline model but is limited to the set of border counties that are contiguous to another county outside the state. "Border-Pair" uses the contiguous county sample and incorporates a vector of county pair by year controls so that the comparison is limited to each county's adjacent counties in a different expansion group. Analysis is weighted by county adult population. Standard errors clustered by state. Figures created using *coefplot*; see Jann (2014).

2011 and 2013. As expected, the difference between expansion and non-expansion counties grows dramatically in 2014 when most states implemented their Medicaid expansion. Early expansion states are not as heavily represented in the contiguous county sample, but the results are otherwise similar in all three specifications.

Figure 4 shows the results of a comparable graphical analysis for uninsurance rates. Regardless of specification, uninsurance rates do not appear to change differentially relative

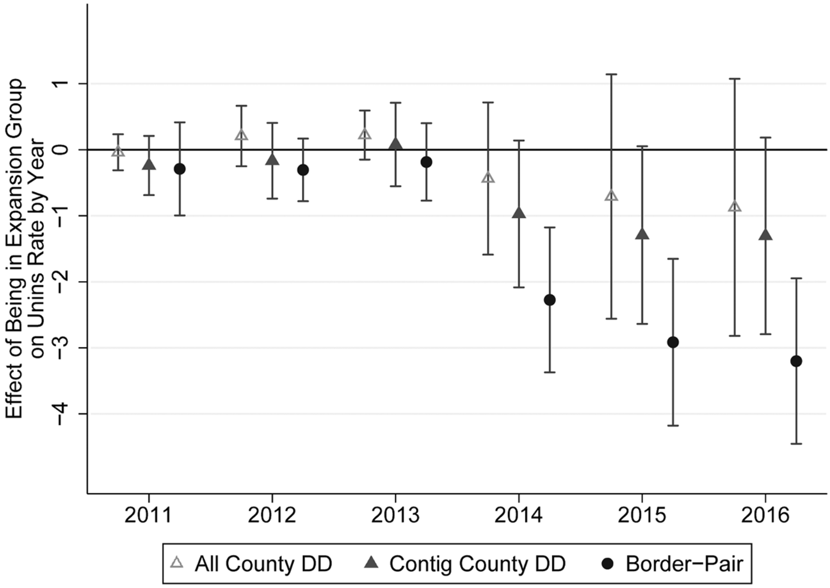

FIGURE 4. Year-by-year effects of being in expansion group on county uninsurance rate. Uninsurance rate is the estimated number of uninsured persons per 100 population. See notes for Figure 3.

to 2010 in expansion versus non-expansion counties prior to 2014. Starting in 2014, there is a relative decline in uninsurance in expansion counties. Notably, the point estimate is largest in magnitude using the preferred border-pair specification. It is possible that this is because comparing within border-pairs controls for unobserved local shocks and better isolates the effect of the Medicaid expansions.

We perform the comparable graphical analysis for the SSI application rate in Figure 5. In the "All County DD" specification we see the suggestion of an upward trend in SSI applications in expansion counties relative to non-expansion counties throughout the 2010–16 period. (Because applications were generally declining, the appropriate interpretation here is that applications declined more slowly in expansion counties.) The same pattern is evident, though not statistically significant, using the contiguous county sample. Once the implied counterfactual is restricted to border counties using the border-pair design, however, the upward trend is no longer evident. Instead, point estimates suggest that expansion counties have SSI application trends that are slightly more negative than those of non-expansion counties, and the two groups are statistically indistinguishable.

Finally, Figure 6 shows the same analysis for SSDI applications. The pattern is quite similar. SSDI applications appear to be on an upward trend in expansion counties relative to non-expansion counties throughout the period using the naive differences-in-differences approach. The border-pair design suggests no differential gap throughout the period.

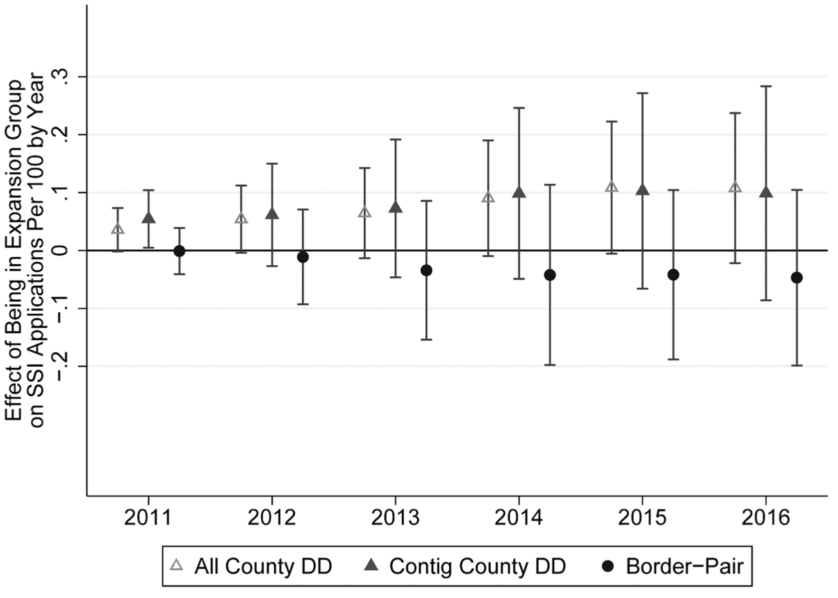

FIGURE 5. Year-by-year effects of being in expansion group on SSI application rate. SSI application rate is the application count for individuals aged 18 to 64 per 100 working-age population. See notes for Figure 3.

B. INSURANCE RATES

We now turn to our main regression analyses. As a first step, we document that the effect of Medicaid on uninsurance seen in the prior literature can be replicated using the county border-pair design. In Table 3, we present the effects of higher non-categorical Medicaid income eligibility limits on uninsurance. Column 1 presents analysis for the all county sample with county fixed effects and year fixed effects, analogous to the standard difference-in-differences model. Column 2 uses the same differences-in-differences specification, but restricts to the smaller sample of contiguous county pairs, and therefore shows (relative to column 1) any differential effects in the border county sample relative to the all county sample. Column 3 incorporates county pair by year fixed effects as described in equation 2 above.

In the differences-in-differences model shown in column 1 of Table 3, the estimated impact of the non-categorical income limit on the fraction uninsured is negative and statistically significant at the 5 percent level. The estimated impact of 0.6 percentage points is similar in magnitude to the 0.9 percentage point effect size in the Courtemanche et al. (2017) naïve differences-in-differences specification.

As we move from the naïve differences-in-differences in column 1 to the preferred county border-pair specification in column 3, the magnitude and statistical significance of the insurance estimates increase, with the largest rise coming between columns 1 and 2. This suggests that despite the smaller sample size associated with the border counties sample, we still have sufficient power to estimate effects of the policy change. The preferred

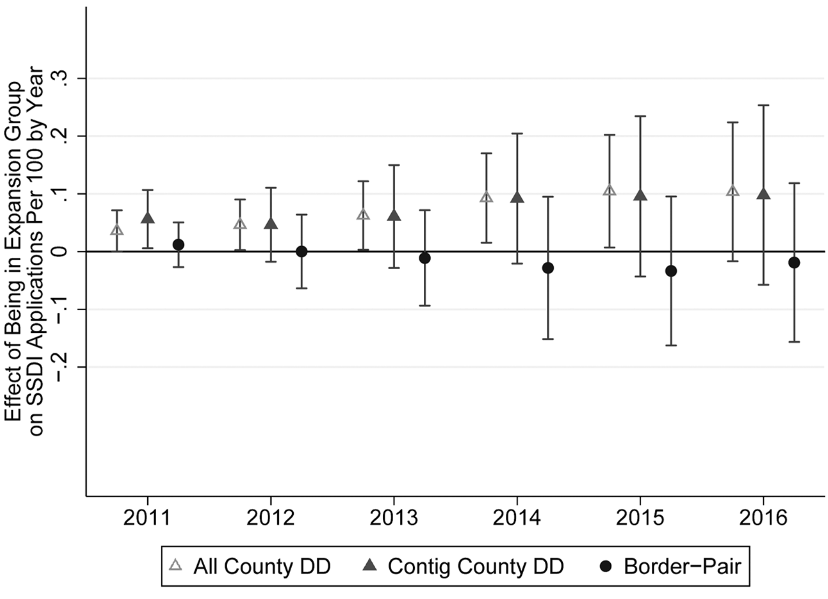

FIGURE 6. Year-by-year effects of being in expansion group on SSDI application rate. SSDI application rate is application count for individuals aged 18 to 64 per 100 working-age population. See notes for Figure 3.

county pair approach shown in column 3 suggests that an expansion in the non-categorical income limit from 0 to 100 percent of the poverty line is associated with a reduction of uninsurance of about 1.6 percentage points. For comparison, the typical expansion was moving from an income limit of 0 percent to 138 percent of the poverty line, and the mean uninsurance rate in the sample in 2010 (prior to the ACA) was 16.0 percent. Therefore, a typical expanding county reduced uninsurance by about 2.3 percentage points relative to an adjacent non-expanding county, around 14 percent of the baseline uninsurance level.

In columns 4 through 6 of Table 3, we use the same set of specifications, but instead examine the percentage of the population with family incomes under 250 percent of the federal poverty level that is uninsured. The coefficients here are larger in magnitude, which is unsurprising since we expect the effects of the ACA Medicaid expansion to be concentrated in the low-income group. Our preferred specification in column 6 includes county pair by year fixed effects, and these results suggest that increasing the Medicaid income limit from 0 to 100 percent of the federal poverty line reduced uninsurance by 2.8 percentage points. Expansion counties moving from 0 to 138 percent of the poverty line would therefore be estimated to have experienced a reduction in uninsurance in the low-income group of 3.8 percentage points compared with bordering counties. This is again around a 15 percent reduction in uninsurance for this group relative to the baseline mean of 26.2 percent uninsured in 2010. Overall, our results in Table 3 show that our contiguous border counties approach finds similar effects of the ACA Medicaid expansion on insurance to prior research using a state differences-in-differences approach.

TABLE 3. Effects of ACA Medicaid income limits on percentage uninsured and percentage low-income uninsured, 2010–16

	All counties sample Percentage uninsured (1)	Contig counties sample Percentage uninsured (2)	Contig counties sample Percentage uninsured (3)	All counties sample Percentage low-income uninsured (4)	Contig counties sample Percentage low-income uninsured (5)	Contig counties sample Percentage low-income uninsured (6)
Non-categorical income limit	−0.574[b]	−1.306[a]	−1.643[a]	−1.481[a]	−2.410[a]	−2.785[a]
	(0.278)	(0.438)	(0.326)	(0.459)	(0.607)	(0.592)
Percentage non-Hispanic black	0.886[c]	0.553	0.331[b]	0.492	0.057	−0.368
	(0.480)	(0.394)	(0.131)	(0.690)	(0.460)	(0.271)
Percentage Hispanic	−0.461	−0.330	−0.067	−0.333	−0.376	0.309
	(0.362)	(0.738)	(0.269)	(0.501)	(0.844)	(0.499)
Percentage ages 50–64	0.036	1.015[a]	0.158	−0.206	0.813[b]	0.007
	(0.511)	(0.302)	(0.213)	(0.613)	(0.389)	(0.372)
Observations	21,630	16,758	16,758	21,630	16,758	16,758
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	NO	YES	YES	NO
County pair × year FE	NO	NO	YES	NO	NO	YES

Note: Dependent variable is the percentage of individuals uninsured in a county or the percentage of individuals with family incomes under 250 percent of poverty uninsured in a county from the Small Area Health Insurance Estimates 2010–16. Estimates are weighted by population. Robust standard errors clustered on state in parentheses. [a]$p < 0.01$, [b]$p < 0.05$, [c]$p < 0.10$.

C. SSI AND SSDI APPLICATIONS

In Table 4 we turn to our main estimates of interest, the impact of higher non-categorical Medicaid income eligibility limits on applications for the SSI and SSDI disability programs. Panel A shows results for SSI applications. As in Table 3, column 1 presents results from our all counties sample with county and year fixed effects, most analogous to the standard difference-in-differences models estimated in the previous literature. It shows a small

TABLE 4. Effects of ACA Medicaid income limits on SSI and SSDI application rates, 2010–16

	All counties sample (1)	Contig counties sample (2)	Contig counties sample (3)
A. SSI applications			
Non-categorical income limit	0.020	0.014	0.004
	(0.022)	(0.030)	(0.021)
Percentage non-Hispanic black	0.033[c]	0.049	0.114[a]
	(0.020)	(0.032)	(0.036)
Percentage Hispanic	0.011	0.052	−0.057[c]
	(0.028)	(0.039)	(0.033)
Percentage ages 50–64	0.072[a]	0.091[a]	0.061
	(0.020)	(0.023)	(0.038)
Observations	21,616	16,758	16,758
B. SSDI applications			
Non-categorical income limit	0.017	0.015	−0.001
	(0.021)	(0.025)	(0.018)
Percentage non-Hispanic black	0.033[c]	0.060[b]	0.099[a]
	(0.016)	(0.023)	(0.027)
Percentage Hispanic	0.012	0.056[c]	−0.034
	(0.026)	(0.028)	(0.028)
Percentage ages 50–64	0.051[a]	0.050[a]	0.045
	(0.016)	(0.018)	(0.029)
Observations	21,616	16,758	16,758
County FE	YES	YES	YES
Year FE	YES	YES	NO
County pair × year FE	NO	NO	YES

Note: Estimates are weighted by working-age population. Application rates are county-year counts of applicants ages 18–64 per 100 working-age population. Application counts between 1 and 9 are coded as 5. Robust standard errors clustered on state in parentheses. [a]$p < 0.01$, [b]$p < 0.05$, [c]$p < 0.10$.

positive estimated coefficient that is not significantly different from zero. Column 2 presents the same specification, but on the set of border counties, while column 3 adds county pair by year fixed effects, so that results are driven entirely from variation within contiguous county pairs. The estimated coefficients decrease in magnitude when we move to the contiguous counties sample in column 2, and fall even more when we include the county pair by year fixed effects in column 3, but all three coefficients are statistically insignificant. Using our preferred specification, the range of coefficients within the confidence interval are −0.04 per 100 to 0.05 per 100 working-age adults, suggesting that we can reject full expansion (i.e., moving from zero to 138 percent of the federal poverty line) effect sizes of 4.8 percent or greater relative to baseline applications.

Panel B presents results for SSDI applications, and shows a similar pattern. None of the models provide evidence that the higher Medicaid income limits created by the ACA Medicaid expansion had impacts on applications to the SSDI program, and we can reject effect sizes of 3.3 percent or greater relative to baseline using our preferred specification.

D. SSI AND SSDI AWARDS

In Table 5, we examine SSI (panel A) and SSDI (panel B) awards in the years 2011–17. Columns 1, 3, and 5 look at the contemporaneous effect of expansions on SSI awards in the three specifications, and none suggest any relationship. Given the length of time between initial applications and ultimate awarding of benefits, in the even-numbered columns we allow Medicaid income limits to affect awards in the current period and also with a one-year lag. This approach also yields no significant results. There are no significant results looking at SSDI awards in panel B. In sum, using a variety of specifications, the results suggest a fairly precisely estimated zero for the relationship between Medicaid and disability awards.

E. ROBUSTNESS

In the Online Appendix, we examine the robustness of results to additional specification decisions. Online Appendix Tables 2 and 3 repeat the analysis for disability applications and awards using a binary expansion indicator rather than a continuous variable. This approach is more consistent with the prior literature. We define a county to have expanded if its non-categorical income limit is higher than zero. This approach, like the continuous variable approach, does not suggest any relationship between ACA Medicaid expansions and disability program applications (Online Appendix Table 2) or awards (Online Appendix Table 3).

In Online Appendix Tables 4 (for applications) and 5 (for awards) , we test the robustness of our results to a number of alternate specifications. For ease of presentation, we only present results from the specification with county border-pair by year effects, and we only present the awards coefficients from regressions that include both the current and the lagged non-categorical income limit. In each table, column 1 presents the baseline results from Tables 4 and 5. In column 2, we omit states that expanded prior to 2014 from the analysis.[24] The early portion of the Medicaid expansion in these states was often less robust

24 These states include California, Connecticut, Delaware, District of Columbia, Massachusetts, Minnesota, New Jersey, New York, and Vermont.

TABLE 5. Effects of the ACA Medicaid income limits on SSI and SSDI awards rates, 2011–17

	All counties sample (1)	All counties sample (2)	Contig counties sample (3)	Contig counties sample (4)	Contig counties sample (5)	Contig counties sample (6)
A. SSI awards						
Non-categorical income limit	0.004	0.0005	0.007	0.001	−0.0001	−0.002
	(0.006)	(0.004)	(0.008)	(0.005)	(0.005)	(0.004)
Non-categorical income limit (lagged)		0.007		0.009		0.004
		(0.004)		(0.006)		(0.004)
Percentage non-Hispanic black	0.015[a]	0.015[a]	0.023[b]	0.023[b]	0.039[a]	0.039[a]
	(0.005)	(0.005)	(0.011)	(0.011)	(0.010)	(0.010)
Percentage Hispanic	0.002	0.002	0.010	0.009	−0.012	−0.012
	(0.007)	(0.007)	(0.008)	(0.008)	(0.010)	(0.011)
Percentage ages 50–64	0.012[a]	0.012[a]	0.019[a]	0.019[a]	0.021[b]	0.020[b]
	(0.004)	(0.004)	(0.007)	(0.007)	(0.008)	(0.008)
Observations	21,616	21,616	16,758	16,758	16,758	16,758
B. SSDI awards						
Non-categorical income limit	0.004	0.0004	0.006	0.003	−0.002	−0.002
	(0.007)	(0.004)	(0.007)	(0.004)	(0.005)	(0.004)
Non-categorical income limit (lagged)		0.005		0.006		−0.001
		(0.005)		(0.005)		(0.004)
Percentage non-Hispanic black	−0.003	−0.003	0.007	0.007	0.015[a]	0.015[a]
	(0.005)	(0.005)	(0.007)	(0.007)	(0.003)	(0.003)
Percentage Hispanic	0.004	0.004	0.017[a]	0.017[a]	−0.004	−0.004
	(0.007)	(0.007)	(0.006)	(0.005)	(0.006)	(0.006)
Percentage ages 50–64	0.013[b]	0.013[a]	0.008[c]	0.008[c]	0.008[c]	0.008[c]
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Observations	19,785	19,785	15,463	15,463	15,463	15,463
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	NO	NO
County pair × year FE	NO	NO	NO	NO	YES	YES

Note: Estimates are weighted by working-age population. SSI awards rate is county-year count of awards for individuals ages 18 to 64 per 100 working-age population, and SSI awards counts between 1 and 9 are coded as 5. SSDI awards rate is count of awards to all ages per 100 total population, and SSDI awards counts are missing for county-year observations with fewer than 10 awards. Robust standard errors clustered on state in parentheses. [a]$p < 0.01$, [b]$p < 0.05$, [c]$p < 0.10$.

than the 2014 expansions in that income limits were often lower than 138 percent and there were sometimes limits on program availability. Excluding early expander states from the analysis makes no substantive difference to the results.

In column 3, we add a control for the unemployment rate. We prefer models that exclude the unemployment rate because employment decisions may respond to the Medicaid expansion directly, so including unemployment may be overcontrolling. Local economic conditions should be largely captured by pair-year controls in our preferred specification. While the unemployment rate is a positive and significant predictor of applications and awards, the coefficients on the non-categorical income limit for both applications and awards remain close to zero and statistically insignificant.

We also explore the impact of missing data on our analysis. In the SSA data, counties with applications or awards between one and 10 are coded as missing for confidentiality purposes (zeros are reported). We set the counts to five in all such counties, which are likely to be the smaller counties in the sample. To check the sensitivity of our results, in column 4 we drop all counties that ever had population below the 25th percentile population in our sample (a population of 11,200), thereby excluding those at risk of data suppression due to small numbers. Again, our results are largely unchanged and continue to show no effect of the Medicaid expansion on disability applications or awards. In column 5 we estimate unweighted regressions (allowing small counties to be weighted equally to larger counties), and continue to find no significant effects. Column 6 controls for state-specific linear time trends and again leaves results virtually unchanged.

Finally, in columns 7 and 8 we follow Maestas, Mullen, and Strand (2014) and examine whether there are heterogeneous responses to the Medicaid expansion by the level of pre-ACA uninsurance. They find that the total number of disability applications (SSDI and SSI combined) increased in counties with relatively high rates of health insurance coverage prior to the Massachusetts reform (consistent with the release of employment lock), while applications for SSI decreased in counties with low rates prior to the reform (consistent with a decrease in the relative value of SSI). Our estimates for applications (in Online Appendix Table 4) and SSI awards (in Online Appendix Table 5) show no evidence of significant differences between counties with high versus low uninsurance rates prior to the Medicaid expansion. The estimates for SSDI awards in column 8 of Online Appendix Table 5 do show a marginally significant negative effect for high-uninsurance counties, consistent with a full expansion effect size of about 4 percent relative to the baseline rate.[25]

F. STATE-LEVEL ANALYSIS

For comparability to the previous literature, in Online Appendix Table 6 we show how results from our county-level analysis on SSI and SSDI applications compare with the state-level equivalents.[26] Columns 1 and 2 repeat the results using a standard county differences-in-differences (Table 4, column 1) and county border-pair design (Table 4, column 3). The

25 The 2010 baseline rate for high-uninsurance counties in the contiguous county sample is 0.32 awards per 100 population.

26 We aggregate our county-level applications and awards data to the state level. State-level applications and awards data are available from the Social Security Administration for SSI, but not for SSDI. For SSI we

next two columns show analogous results using state-level data. Column 3 of Online Appendix Table 6 presents the standard state difference-in-difference estimates. Column 4 uses only variation in Medicaid income eligibility limits between contiguous state pairs, using the same idea as in the county border-pair design, although it exploits different variation than in the county version of the analysis. For applications, while the straight difference-in-differences in column 1 (for the county data) and column 3 (for the state data) tend to show positive estimated coefficients, coefficients turn negative when the border-pair by year fixed effects are included. These are generally not statistically different from zero (but become marginally significant and negative for state-level SSDI applications).

Online Appendix Table 7 presents the same exercise for SSI and SSDI awards and shows similar patterns. Most specifications show statistically insignificant impacts, with the exception of the state border-pair design suggesting statistically significant 4 percent reductions in SSI awards and 3 percent reductions in SSDI awards associated with Medicaid expansion. Combined with the results in Online Appendix Table 6, it appears that the state border-pair design suggests a small reduction in disability programs associated with Medicaid expansions, but neither the preferred county border-pair design nor the straightforward difference-in-differences design shows significant impacts.

VII. Discussion and Conclusion

In this paper, we use a contiguous county approach to examine whether the ACA Medicaid expansion affected disability program applications. Despite strong evidence of increases in insurance coverage due to the Medicaid expansion using the county border discontinuity identification strategy, there is little evidence supporting a relationship between Medicaid availability and the decision to apply for the SSI or SSDI disability programs. We also find no significant effects of higher non-categorical Medicaid income eligibility limits on SSI or SSDI awards.

Theory predicts possible countervailing impacts of Medicaid availability on the decision to apply for Medicaid. Our preferred estimates indicate that there was little or no net impact of the Medicaid expansion portion of the Affordable Care Act on disability program applications, and consequently no effect on awards. These null results are robust across most specifications and models, and are fairly precise zeros. The confidence intervals for our preferred specifications rule out effect sizes of 5 percent of baseline application rates in either direction for SSI and SSDI.

Despite the lack of a relationship with disability programs, there is potential for spillover effects across other safety net programs. For example, Schmidt, Shore-Sheppard, and Watson (2019) examine the impacts of the ACA Medicaid expansion on participation in the Supplemental Nutrition Assistance Program (SNAP) and receipt of the Earned Income

compared our aggregated data with the published SSI counts, and while they differ slightly because of differences in the reporting time frame (our Disability Research File estimates are reported in June of the following year, while the published SSI estimates are reported as of December of the given calendar year), discrepancies are generally 1 percent of the total or smaller.

Tax Credit (EITC), and find results suggesting that the Medicaid expansion increased SNAP and EITC participation in counties that expanded relative to nearby counties that did not expand. Considering such spillover effects may be important when assessing the full costs and benefits of the ACA Medicaid expansion.

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