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The Rent is Too Damn High and the Coverage is Too Damn Low: Evidence from Medicaid Expansion and Eviction Rates

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The Rent is Too Damn High and the Coverage is Too Damn Low:

Evidence from Medicaid Expansion and Eviction Rates

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Abstract

In this paper, I use a novel dataset on evictions and a quasi-experimental research design to shed light on the relationship between health insurance and housing stability. I exploit variation in Medicaid expansion implementation to measure the expansion's impact on county-level eviction rates. In my preferred difference-in-differences specification, I estimate that the expansion decreased eviction rates by 12.5%, leading to one fewer eviction per 400 renting households. As the 95% confidence interval on this estimate ranges from -25.7% to 0.7%, I fail to reject both that the expansion had a more substantial negative impact or that it had no impact. The expansion appears to have a heterogeneous impact based on county characteristics. For example, it appears to have a larger impact on rent-burdened counties. Counterintuitively, I find that a county's baseline uninsured rate has little relationship with the impact of Medicaid expansion on the county's eviction rates. My paper adds to a growing literature on the impact of Medicaid expansion on a variety of labor, health, and economic outcomes and is the first to use this national dataset of evictions.

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1 Introduction

Until recently, no public national dataset on evictions existed. However, data from The Eviction Lab at Princeton University now indicate that in recent years, over a million court-ordered evictions occurred in the United States annually, and, consequently, about 2.5-3.0% of renting households faced an eviction (see Appendix A). Moreover, these estimates are a lower-bound on the prevalence of eviction due to the challenge of obtaining nationwide data from court records and to the omission of informal evictions, which are those done outside formal court procedures. This prevalence should trouble policymakers as existing literature has made clear the negative consequences of eviction and housing instability on individuals, families, and communities [Maqbool et al., 2015; Fowler et al., 2015; Desmond and Kimbro, 2015; Greiner et al., 2012].

In this paper, I theorize that having health insurance can lower the likelihood of eviction for an individual because of an individual's ability to better withstand health shocks financially and physically. Withstanding shocks proves important for low-income renters as non-payment of rent is the lead immediate cause of eviction [Desmond, 2012]. To test my theory, I examine the impact the Patient Protection and Affordable Care Act's (ACA) Medicaid expansion has had on county-level eviction rates. In vastly different states and localities that expanded Medicaid, trends in eviction rates seem to have changed after Medicaid expansion. In Figure 1, for example, it is evident that in 2014, eviction rates began decreasing at a faster rate than in previous years in both Kanawha County, West Virginia, the most populous county in the state, and in Genessee County, Michigan, home of

Flint. One possibility for the trend breaks is Medicaid expansion, as both states expanded Medicaid in 2014. However, other varying factors could play a role. I rely on various econometric methods to isolate the causal role of Medicaid expansion.

To estimate the impact of expansion, I first use a difference-in-differences (DD) model that utilizes variation in Medicaid expansion implementation. I repeat the model across several specifications, and I replicate the DD model using data only from commuting zones (CZs) that stretch across multiple states which have different expansion statuses. Second, I test for the effect of the treatment intensity of Medicaid expansion by using a difference-in-difference-in-differences (DDD) model that accounts for a county's pre-treatment uninsured rate. Third, I use the interaction terms from the DDD model as instrumental variables to estimate an elasticity of uninsured rates and eviction rates. Lastly, I present a synthetic control model in Appendix B as a robustness check to my regression methodology.

In my preferred DD specification, I find that Medicaid expansion reduced eviction rates by 12.5%. I fail to reject that the expansion had a more substantial negative impact or that it had no impact as the 95% confidence interval on this estimate ranges from -25.7% to 0.7%. Across specifications and robustness checks, I find a consistent, statistically insignificant negative estimate. The expansion appears to have a heterogeneous impact on eviction rates based on county characteristics. Notably, I find that the expansion is associated with an 18.7% decrease in eviction rates in counties whose median rent as percent of income is in the top quartile. The 95% confidence interval on this estimate ranges from -42.7% to 5.2%. My DDD model reveals that a county's baseline uninsured rate has little relationship with the Medicaid expansion's effect on eviction rates. This finding differs from existing Medicaid expansion literature that examined other outcomes. Lastly, in my instrumental variable (IV) approach, I find a statistically insignificant relationship between health insurance and eviction rates; however, the instruments in this model may fail the exclusion restriction.

The connection I theorize between health insurance and housing stability for low-income individuals extends that of Gallagher and Grinstein-Weiss [2017]. Gallagher and Grinstein-Weiss [2017] describes two channels through which health insurance can impact home mortgage payments, and this framework is helpful for thinking about rent payments, too. First, insurance protects against a "medical expenditure shock." Through this channel, health insurance protects a household's liquid assets from health shocks. This is pertinent for renters as rent burden, a situation in which one pays over 30 percent of her income to rent, has increased in America. In the past two decades, the percentage of rent-burdened families has increased from 43 to 54 percent and, furthermore, now 30 percent of renters pay half of their income to rent [Desmond, 2015].

The second channel through which health insurance can reduce the likelihood of eviction is by stabilizing or lifting household incomes. Health insurance can enable workers to increase their labor productivity and increase their wages. With access to proper healthcare and preventative care, employees will have better health outcomes and, consequently, be more productive workers. In addition, health insurance can provide stability by smoothing out medical payments. In theory, by providing financial stability, health insurance can enable households to make forward-looking financial decisions and better meet their financial obligations, including rent payment.

To measure the impact of health insurance on eviction, I focus on the Medicaid expansion provision of the ACA. The expansion of Medicaid to populations under 138% of the Federal Poverty Line (FPL) proved one of the most impactful provisions of the ACA. By the end of 2016 nearly 12 million Americans who were newly eligible for Medicaid obtained insurance [Sommers and Epstein, 2017]. In the years immediately before and after the expansion, though, other trends certainly could have impacted eviction rates. For example, the recession and economic recovery had a massive impact on both households' incomes and the housing market. Perhaps, then, decreasing eviction rates after 2014 would be due to improving economic conditions rather than increased access to health insurance. In addition, some localities have changed local laws and ordinances regulating eviction. Measuring the empirical impact of Medicaid expansion on eviction rates requires disentangling these trends.

To do so, I rely on geographic variation in the implementation and treatment intensity of the Medicaid expansion. The implementation of Medicaid expansion varied in important ways. By the end of 2017, 33 states, including the District of Columbia, expanded Medicaid. Although most expansion states implemented the reform in January 2014, Michigan, New Hampshire, Pennsylvania, Indiana, Alaska, Montana, and Louisiana all implemented the expansion at other dates (see Table 1). Additionally, pre-ACA variation in insurance rates and poverty rates determine the potential impact of Medicaid expansion. If a state had no population between 100% and 138% of the FPL, then the expansion would have no first-order effect on the uninsured rate. Likewise, a state with a low pre-treatment uninsured rate would have a smaller potential coverage impact from the expansion than a state with high pre-treatment uninsured rates. Moreover, states have had local health care reforms, most notably Massachusetts, which implemented its own broad health care reform, that impact potential treatment intensity.

I am able to isolate the impact of Medicaid expansion on eviction rates through my various econometric approaches utilizing county-level data on uninsured rates and eviction rates from 2005 to 2016. I use Census Small Area Health Estimates (SAHIE) data for health insurance and a novel dataset on evictions from The Eviction Lab. The data I use for my main empirical specifications include about 87% of counties nationwide, and nearly 50% of counties have data for all years between 2005-2016. In addition, I use a variety of demographic and economic control variables from the Census American Community Survey and the Bureau of Labor Statistics. I also vary my analysis with county fixed effects, time fixed effects, and geographic linear time trends.

My results suggest that the Medicaid expansion led to a decrease in county-level eviction rates. However, due to large standard errors, I fail to reject that the expansion had a more substantial negative impact or that it had no effect. In my preferred DD model, I find that the expansion reduced eviction rates by 12.5%. In my raw eviction data, states that expanded Medicaid had over 440,923 evictions in 2013, so a reduction by this percentage would amount to more than 55,000 fewer evictions per year. In addition, if this estimate holds, 55,000 is a lower bound for the reduction in total evictions. First, my eviction dataset omits informal evictions, which research limited to Milwaukee suggests account for about 48% of forced moves [Desmond, 2016]. Second, my eviction dataset also undercounts formal evictions. Due to challenges in collecting court records, the total count of evictions in some counties is far below intuitive estimates and the dataset lacks statistics from every county.

Although my preferred DD estimate is statistically insignificant, I find consistent, negative estimates using several robustness checks and alternative specifications. The results hold when varying the inclusion of demographic controls, economic controls, and geographic linear time trends. Furthermore, I balance my dataset by dropping counties that lack eviction data across 2005-2016. In another specification, I use a SAHIE dataset with data from 2008-2016 for uninsured rates for people under 400% of the FPL. When I drop Massachusetts and states that expanded in the middle of a year, I again find statistically insignificant negative estimates.

The impact of the Medicaid expansion appears to be heterogeneous depending on county characteristics. I explore this heterogeneity by restricting my sample based on counties' median rent as percent of income, total population, and classification. Intuitively, counties with a greater rent burden appear to benefit more from the expansion as they have a greater reduction in eviction rates. In counties in the top quartile of median rent as percent of income, the expansion appears to reduce eviction rates by 18.7%. There is no evident connection between reductions in eviction rates based on the total population of a county or whether the county is urban.

Following the methodology of Yagan [2017], I also repeat my DD model restricting my sample to counties in CZs that stretch across state borders, in which at least one state expanded and one did not. This analysis includes 43 CZs and

221 counties. I again find consistent negative but statistically insignificant estimates. However, when I restrict this sample further to omit commuting zones that stretch across three states, I find a consistent, statistically significant effect. This sample includes 38 CZs and 185 counties. These results further suggest that the expansion had a heterogeneous impact on eviction rates and that certain county characteristics could lead to a greater relationship between insurance coverage and eviction rates.

Using my DDD model, I am able to rule out that the baseline uninsured rate of a county related to the impact of Medicaid expansion on the county's eviction rates. In my preferred specification, the coefficient on my DDD interaction of a county's baseline uninsured rate, its expansion status, and whether it is a post-treatment year, is statistically indistinguishable from zero. Moreover, the coefficient is of a small magnitude, about 0.01. This result runs counter to much of the existing literature on Medicaid expansion that suggests the potential treatment intensity of Medicaid expansion is often a significant in measuring the expansion's impact on a variety of other outcomes.

Lastly, I use the DDD equation as a first-stage equation in an IV model. Instrumenting for health insurance coverage, I find a statistically insignificant relationship between the uninsured rate and eviction rates. When I use both the triple interaction term and an interaction of baseline uninsured rate and post-treatment year as instruments, I find that a decrease in uninsured rates is associated with an increase in eviction rates. While using just the triple interaction term as an instrument, though, I find the opposite relationship. These instruments likely fail to pass the exclusion restriction as the ACA could have impacted eviction rates in ways other than insurance coverage.

My preliminary analysis suggests that the Medicaid expansion led to fewer evictions, but it is inconclusive. This analysis relies on a novel dataset of evictions that has shortcomings. First, several states have undercounted evictions for a variety of reasons, such as missing county data or an inability to access all records from a given county. However, in my analysis this data limitation is mitigated by my fixed effects. Second, and more importantly, some locations have varying levels of data collection across time. I drop these observations from the dataset in my regression analysis. With a more complete and accurate dataset on evictions, my analysis should be replicated and updated with 2017 data to also measure potential lag effects.

I organize the rest of my paper as follows. Section 2 provides a background on broader causes of eviction, the prevalence of eviction, the ACA, and existing literature on Medicaid expansion. In Section 3, I summarize my data sources. Section 4 includes my different empirical approaches and specifications. Section 5 summarizes my regression results. I conclude and discuss policy implications in Section 6.

2 Background

In this section, I discuss broader causes of eviction and why the prevalence may be higher for African-Americans. Next, I provide a brief overview on the prevalence of eviction today. I also summarize existing literature that elucidates the negative consequences of housing instability on individuals, families, and communities. I then provide a background on the ACA's marketplace subsidies and Medicaid expansion. Lastly, I conduct a meta-analysis of existing research on the effect of Medicaid expansion on a variety of outcomes.

2.1 Historic and Present Causes of Eviction Today

Three major factors contribute to the prevalence of eviction today, and, in particular, to the prevalence for African-Americans. First, incomes for low-income individuals have stagnated in recent decades, a well-documented phenomenon in recent economic literature. Second, while incomes have stagnated, rent prices have increased in much of the country. Third, inequality and segregation in historic housing policy have played a role in the concentration of eviction in African-American neighborhoods [Desmond, 2016].

In recent decades, the bottom half of the income distribution has seen little economic opportunity and growth. This fact proves important for eviction as one can view non-payment of rent both as a function of low incomes and of rising rent. While the top decile and top 1% have seen incomes explode in recent decades, from 1980 to 2014, the average pre-tax income of the bottom 50% of individual earners stagnated [Piketty et al., 2016]. Moreover, the average post-tax income of the bottom 50% of adults increased by a far smaller magnitude than higher income groups in the same time period. Although government transfers are progressive, they have not led to equitable distribution of economic gains [Piketty et al., 2016]. Specifically for renters, the median income was just over $37,000 (in 2012 dollars) in 2000 [noa, 2013]. By 2012, that income had decreased to under $33,000.

These income trends become more problematic for low-income renters when coupled with trends in rent prices. While incomes have stagnated or declined for low-income individuals, rent prices have risen, and there is greater demand in the renting market. From 2000 to 2012, the median rent increased from about $800 to $850 dollars [noa, 2013]. Since the recession, demand has increased in the rental market. Vacancy rates have declined as more people have shifted from home-owning to renting. On average, median rent prices have outpaced inflation, and in places with high employment growth, increases in rent prices have far outpaced inflation [noa, 2013]. Adding to the market pressure, construction is at a historically low level. After the recession, America consequently faced historic levels of rent-burdened households, as both incomes stagnated and rents rose. Today, fewer than one in four renting households eligible for housing assistance receive any [noa, 2013].

However, the prevalence of eviction is not just driven by market forces or individuals' decisions in the private market. Instead, it has roots in government policy which created and perpetuated inequity and segregation. Present eviction conditions illustrate the role local, state, and federal government played in creating today's prevalence of eviction. Evictions are concentrated in African-American neighborhoods and, in particular, single African-American women face a disproportionately high number of evictions [Desmond, 2016]. *The Color of Law* provides an in-depth history on how New Deal policies often worked to suppress relative African-American wages, how discriminatory policy kept African Americans from homeownership, and how government housing construction perpetuated neighborhood segregation [Rothstein, 2017].

2.2 The Prevalence of Eviction

2.2.1 Prior Attempts at Measurement

With limited data, some researchers have tried to estimate the prevalence of eviction or provide some measurement as to the scope of evictions. Hartman and Robinson [2003] estimates that there are millions of annual evictions in America. More recent surveys indicate that renters in over 2.8 million homes report feeling they would be evicted soon [Desmond and Gershenson, 2017]. Through court data analysis and the Milwaukee Area Renters Surveys (MARS), Matthew Desmond provides an accurate measurement of evictions in Milwaukee. According to court data, One-in-fourteen renting households in predominantly black inner-city neighborhoods face a formal eviction [Desmond, 2012]. Survey data, which also accounts for informal evictions, indicates that about one-in-eight renting households annually faced eviction in Milwaukee from 2009-2011 [Desmond, 2016]. Unfortunately, the measurements from Milwaukee prove challenging to extrapolate with external validity because of national differences in local housing policy, economic conditions, rent prices, and demographics.

Measuring eviction has proved challenging for two reasons: 1) Unavailable and/or disaggregated court data and 2) inadequate measures of informal evictions. Many states deny access to statewide court databases, lack these databases, or have incomplete data that fail to indicate if an eviction occurred in a given case. Additionally, in states that lack a statewide database, court record data collection and policies regarding data access vary both across localities and, sometimes, within them. For example, Bexar County, Texas has electronic case records but each Justice of the Peace Court has jurisdiction over its own data and data collection methods. On the other hand, Travis County, Texas, lacks electronic case records. Even in localities with electronic records, determining if a case resulted in an actual eviction rather than a money judgment or another outcome can be difficult because of how courts internally define judgment outcomes.

Another issue in measuring the prevalence of eviction is the existence of informal eviction. Informal evictions are characterized by any eviction process occurring outside a formal court procedure. These can take many forms. A landlord could pay a tenant to move out or a landlord could create poor conditions that drive a tenant out. For example, in *Evicted*, a landlord removed a tenant's door, giving the tenant the option of leaving or living without the safety of a front door [Desmond, 2016]. Though some places like Missouri and Boston have outlawed informal evictions, they are still commonplace in much of the country.

The Census Bureau has attempted to estimate informal evictions through the American Housing Survey. However, these Census estimates prove unreliable. Often, tenants fail to recognize their informal evictions as what researchers would define as evictions. A landlord paying a tenant to leave or removing a door might not be defined as an eviction by a tenant. To account for the variation in informal evictions and to get an accurate estimate of evictions, MARS asked over 250 questions. The Census American Housing Survey plans to adopt the questions from MARS and this should provide reliable national estimates of eviction in the future.

2.2.2 State- and County-Level Eviction Estimates from LexisNexis

The Eviction Lab at Princeton University has begun collecting nationwide eviction data in an attempt to provide the first comprehensive dataset on the prevalence of eviction. In this paper, I use raw data the Eviction Lab acquired from the vendor LexisNexis. LexisNexis collects individual formal eviction records from across the country using a variety of private methods.

For national, state-level, and county-level estimates, the LexisNexis raw data provides a lower bound to actual eviction counts. Each eviction count recorded by LexisNexis tracks to a court-mandated eviction. Consequently, in each county the LexisNexis eviction counts provide either wholly accurate eviction counts, or more likely, lower bounds. One can conclude that these estimates are lower bounds because of a probable inability of LexisNexis to access all cases.

Issues with the LexisNexis data prevent cross-state comparisons and complete reliability in eviction counts, but the data still enable analysis across time. First, as with any court data, this dataset omits informal eviction. For my analysis, I assume the ratio of formal to informal eviction in any given county remains constant over time. Second, a variety of data collection challenges exist, ranging from the inability of the vendor to obtain certain counties' data to consistently low eviction counts in other counties. For example, the number of evictions in Arkansas, as seen in Table 17, are too low to follow intuition and prior research on the prevalence of eviction. Third, some states and counties have varying levels of data collection across times that prevent accurate analysis. I omit these data, which I outline later, from my econometric analysis.

The national total raw eviction counts in the LexisNexis data can be found on

Table 16. I calculate an eviction rate in my analyses as the number of evictions per 100 renting households. Following the methodology of the Eviction Lab, I rely on the Census American Community Survey (ACS) and the 2010 Census for county-level renting household estimates. For each year before 2010, I use the 2005-2009 ACS 5-Year Estimates, for 2010 I use the Census, and for each year between 2011 and 2016 I use the 2011-2015 5-Year Estimate. Table 16 only includes the number of renting households for counties in which LexisNexis provided data. I illustrate the dataset's coverage in Figure 13. Since 2005 this dataset includes over one million evictions per year except for 2016, in which the number of evictions is slightly under one million.

These national estimates still lack data from several counties and from all of North Dakota and South Dakota. Moreover, many states' eviction counts are clearly underestimated. Table 17 provides annual eviction rates for each state since 2012. The eviction rate is calculated per 100 renting households and includes only the number of renting households for counties with eviction data. For example, Arkansas, California, New York, and Vermont all have low eviction rates that indicate low data coverage in those states. Table 17 also reveals examples of varying levels data collection of across time within a state. An illustrative example is the change in the eviction rate in South Carolina from 2015 to 2016. This represents a change in data collection procedure rather than a dramatic change in eviction rates. Cross-state comparison in eviction rates proves unreliable; however, after accounting for intrastate varying levels of data collection, one can compare changes across counties over time.

Although these data are administrative court records, it is important to note that varying state and local eviction laws and procedures also play a role in eviction counts for each county. For example, in an eviction filing, landlords must usually provide a notice for termination without cause or a notice for termination with cause. Depending on local laws, the time frame in which a landlord must provide that notice varies. Consequently, the length of a formal eviction varies often from weeks to months across localities. Another source of variation is that some localities, such as San Francisco, have Just Cause Eviction Ordinances, which outline an exhaustive list for which a landlord can evict a tenant. Moreover, some areas, such as Missouri, go further with tenant protection, requiring all evictions to go through a court-procedure, thereby disallowing informal eviction.

2.3 Housing and Well-Being

The prevalence of eviction proves concerning for policymakers given existing research tying stable housing and measures of well-being together. Research links housing stability, or the lack thereof, to health, economic, and educational outcomes of individuals, families, and communities. Safety and stability reduce stress and prevent potential negative health outcomes from health-risks, like mold or Asbestos. Stable housing enables adults to have better prospects for stability in their employment. Lastly, stable housing ensures children avoid the trauma of eviction and adds continuity to schooling and social ties.

A clear relationship exists between housing and adult health outcomes. Low-quality housing exposes families to physical health risks and increases stress levels [Maqbool et al., 2015], "duty-free" friendships, and lower levels of mental well-being [Oishi, 2010]. As a traumatic event, eviction has been linked to an increased likelihood of suicide in adults [Fowler et al., 2015]. In addition, experiencing an eviction impacts mental health and creates an increased likelihood of depression that can potentially last for multiple years [Desmond and Kimbro, 2015].

Eviction also has a two-way relationship with economic well-being. A cause for the prevalence of evictions is the affordable housing crisis. From 1991 to 2013, the percentage of renting households that spent less than 30 percent of their income on housing fell from 54 to 43 percent, while the percentage of those paying over half their income rose from 21 to 30 percent [Desmond, 2015]. Once evicted, a family's economic situation becomes more precarious. Eviction records can prevent families from receiving public housing assistance and can damage their credit rating [Greiner et al., 2012]. Forced displacement also leads to families relocating in neighborhoods that are poorer and have more crime [Desmond and Shollenberger, 2015]. Moreover, when people are evicted in poor neighborhoods but cannot afford to move elsewhere, community instability increases. Residential mobility within neighborhoods is associated with an increased risk of neighborhood violence [Sharkey and Sampson, 2010]. Poor neighborhoods and violence intuitively lead to fewer economic opportunities, fewer social ties, less outside investment, and decreased access to jobs.

Evictions not only have a negative impact on adults, but also they negatively impact children. In fact, evictions disproportionately happen to households with children. Neighborhoods with children have more evictions, and a household with children is more likely to receive an eviction judgment in court [Desmond et al., 2013]. Without stable housing, a poor child's ability to stay in school and develop academically suffers [Ziol-Guest and McKenna, 2014]. Homeless students and students with multiple housing moves perform worse on standardized tests, have worse school attendance, are more likely to drop out, and have delayed literacy skills [noa, 2010; Pribesh and Downey, 1999]. Studies have linked children with multiple housing moves to increased levels of adolescent violence and health risks [Haynie and South, 2005; Dong et al., 2005].

Given limited data, much of the existing eviction literature has relied on the selection on observables assumption. Rather than examining a complete renting population that has both evicted and non-evicted households, researchers have had to rely solely on data from evicted households or by attempting to create control groups. With access to a larger dataset and with a quasi-experimental research design, I am able to provide a causal estimate for my outcome.

2.4 The Patient Protection and Affordable Care Act (ACA)

In this paper, I examine the potential impact health insurance coverage can have on eviction rates by using the introduction of the ACA. Today, over 20 million more Americans have health insurance because of the ACA's Marketplaces and Medicaid expansion. Previously, Medicaid typically covered children, pregnant women, older adults, and disabled adults. The expansion aimed to provide Medicaid to all Americans under 138% of the FPL. However, the Supreme Court case *National Federation of Independent Businesses v. Sebelius (NFIB)* enabled states to opt-in to Medicaid expansion rather than abide by the ACA's original requirement that all states expand. In addition, The ACA provided subsidies for families with an income under 400% of the FPL that purchase health insurance on the private market.

2.4.1 Marketplace Subsidies

Marketplace subsidies constituted a major provision of the ACA intended to increase coverage for low-income individuals buying private insurance. Individuals between 100% and 400% of the FPL are eligible for subsidies for private health insurance on ACA marketplace exchanges. Families that have an income over 400% of the FPL, adjusted for family-size, are ineligible for subsidies. Families under 100% of the FPL in non-expansion states or under 138% of the FPL in expansion states are eligible for Medicaid.

Subsidies are determined by a family's income as a percentage of the FPL and their area's premiums. Depending on a family's income, individuals are responsible for paying a certain percentage of their total income towards the cost of health insurance. The lower bound is 2% and the upper bound, for those closest to 400% of the FPL, is 9.5%. Subsidy amounts vary widely across and within states due to differences in premium costs. The subsidies are a function of the price of the second lowest cost silver tier plan on the marketplace and the maximum premium payment the individual must pay. Individuals in high-cost areas thus receive larger subsidies.

2.4.2 Medicaid Expansion

Under Medicaid expansion, the federal government agreed to cover all the costs of the expansion until 2016 and beyond 2020 cover only 90% of the costs. After *NFIB*, states could decide whether to opt-in on expanding Medicaid. Consequently, today, Medicaid expansion status varies across states. Thirty-three states, including the District of Columbia, have expanded Medicaid. Medicaid expansion proves to be a crucial part of the ACA because of the specific population it targets, the number of individuals it covers, and because of Medicaid's impact on health outcomes.

Prior to the ACA, Medicaid played an instrumental role in the American healthcare system. In the Fiscal Year 2011, Medicaid covered an estimated 68 million Americans and garnered nearly $400 billion of expenditures [Paradise, 2015]. Federal policy dictated that states provide Medicaid for the following groups that had incomes beneath 100% of the FPL: children, pregnant women, parents of dependent children, individuals with disabilities, and adults over 65 years-old. Beside this mandate, variation existed across states in Medicaid eligibility, the coverage of services, and reimbursement policy. In FY 2011, children made up 48% of Medicaid enrollees, adults made up 27%, the elderly made up 9%, and the disabled made up 15%. The greatest proportion of spending, 42%, went toward disabled individuals [Paradise, 2015].

A large body of existing literature has examined the impact of Medicaid on both children's and adults' health outcomes and healthcare utilization. As compared to uninsured children, those children with Medicaid are more likely to have a usual source of care, report easier access to specialists, receive regular checkups [Kenney and Coyer, 2012]. In addition, children with Medicaid coverage are less likely than low-income uninsured children to have unmet dental or prescription drug needs because of costs [Howell and Kenney, 2012]. As with broader Medicaid, variation exists across states in eligibility and services for children. Under the State Children's Health Insurance Program (CHIP), states had the option to enroll children using their existing Medicaid program, a separate non-Medicaid program, or a combination of the two [Howell and Kenney, 2012]. States also have limited control over enrollment processes, payment rates, cost-sharing requirements, and managed care programs.

Medicaid also has similar results for adults. As compared to the uninsured, Medicaid recipients have better and increased access to and use of care [Long et al., 2005]. The level of access and care are similar to a comparable low-income population with private insurance. Medicaid has also been shown to have a significant impact on health outcomes. Medicaid expansions were associated with reductions in mortality rates, especially for older adults, nonwhites, and individuals from poor areas [Sommers et al., 2012]. Prior Medicaid expansions also decreased rates of delayed care because of costs and improved self-reported health statuses [Sommers et al., 2012]. The Oregon Health Experiment indicated that Medicaid also significantly improved mental health outcomes and eliminated catastrophic medical expenses [Baicker et al., 2013]. However, Medicaid has had no clear impact on employment or earnings, although evidence suggests it increases the probability of receiving food stamps [Baicker et al., 2014].

The ACA's Medicaid provision aimed to expand the program to a new population. Non-elderly adults were likely to benefit the most as CHIP already covered most children at this income level. Before *NFIB*, the Congressional Budget Office (CBO) projected that 16 million people would gain insurance through Medicaid expansion; however, the estimate dropped to 11 million after the ruling [Duggan et al., 2017]. Several papers have estimated the coverage gains to date from the expansion and I summarize this literature in Section 2.4.3.

The effect of Medicaid expansion on coverage has varied across states for reasons beyond just implementation. First, pre-expansion insurance and poverty rates have a large impact on the treatment intensity. For example, Massachusetts, a state with significant health care reform in 2006, would be expected to have smaller insurance gains from the expansion because its uninsured rates were already low. A state with a small share of its population between 100% and 138% of the FPL would also likely have smaller coverage changes because less of its population would become eligible for Medicaid. Second, several states expanded using a waiver from Section 1115 of the Social Security Act. This waiver, granted by the Secretary of the Department of Health and Human Services, enabled states to try an "experimental, pilot, or demonstration project" that differed from generic Medicaid provisions. States using a Section 1115 waiver could have limited variation in eligibility, provider payments, and cost-sharing that could potentially cause variation in enrollment relative to other expansion states. Information on individual states' expansion status, date of expansion, and use of a Section 1115 waiver can be found listed on Table 1 and illustrated in Figure 2.

2.4.3 Meta-analysis of Medicaid Expansion Literature

Variation in the implementation of Medicaid expansion enables researchers to use it as a quasi-random experiment. Although no literature exists examining the relationship between expansion and eviction, a growing body of work examines the impact of Medicaid expansion across several outcomes using methodologies similar to mine. Existing literature on the topic focuses on outcomes in four categories: Insurance coverage, the labor market, health outcomes, and financial stability. A meta-analysis of literature in these categories follows and I summarize it in Table 2.

Using DDD models, researchers have studied the causal impact of Medicaid expansion on broader insurance gains from the ACA. Duggan et al. [2017] finds that a substantial portion of insurance gains since 2013 are due to the ACA and areas with lower baseline uninsured rates had larger increases in coverage. Frean et al. [2017] finds that about 60% of the insurance gains from the ACA are a product of Medicaid expansion and half of these expansion gains are from previously-eligible individuals. Courtemanche et al. [2016] estimates that the ACA increased the proportion of residents with insurance by nearly double the amount in expansion states.

A growing literature has also analyzed the expansion's effect on both the labor force and the labor market. Two papers have examined effects to the labor force. Slusky and Ginther [2017] utilizes the Current Population Survey (CPS) to determine that Medicaid Expansion reduced the prevalence of divorces by 11.6% among college educated 50-64 year olds. Goodman [2017] tests for the impact of the expansion on migration, answering whether a state's expansion status could create an incentive for migration. The paper rules out a migration effect that would meaningfully change the number of enrollees in expansion states, indicating that the decision to expand does not create a negative fiscal externality through migration.

More researchers have focused on the early impact of the Medicaid expansion on labor market outcomes. The CBO originally predicted negative employment effects because of the ACA. Duggan et al. [2017] finds that the expansion had little aggregate labor market effects; however, the aggregate impact may mask heterogeneity in local labor markets. Gooptu et al. [2016] also rules out significant changes in employment, job switching, or full- versus part-time employment due to expansion. Frisvold and Jung [2017] estimates the expansion did not impact labor force participation, employment, or hours worked. Lastly, Kaestner et al. [2015] finds the expansion had little impact on work effort and find a small, but insignificant, increase in work effort due to the expansion.

Unlike with the labor market, the Medicaid expansion has had a clear causal effect on both individual health behavior and on broader healthcare delivery systems. Maclean et al. [2017] estimates that the expansion increased smoking cessation prescriptions by 36% and total Medicaid-financed payments for smoking cessation prescriptions by 28%. Similarly, Maclean and Saloner [2017] finds that in expansion states relative to non-expansion states, Medicaid-reimbursed prescriptions for substance use disorder medications increased by 43%. Ghosh et al. [2017] concludes that Medicaid-financed prescription utilization increased by 19 percent in expansion states relative to non-expansion states within the first 15 months of expansion. Medicaid Expansion also appears to have increased the use of certain forms of preventative care [Simon et al., 2017]. On the other hand, Courtemanche et al. [2017b] finds that the expansion had no impact on risky behavior or self-assessed health in their full sample.

The expansion not only affected individual action, but also it impacted the broader healthcare delivery system. Dranove et al. [2016] estimates that the expansion decreased uncompensated care costs nearly 25%, or one percentage point of total hospital operating costs. Other literature points to an increased strain in the healthcare system because of the expansion. Courtemanche et al. [2017a]

finds that ambulance response times slowed and the ACA, in part because of the expansion, added strain to emergency response systems. Moreover, Nikpay et al. [2017] concludes that, consistent with survey results, the expansion increased the use of emergency department visits. Most recently, Loehrer et al. [2018] utilizes data from nearly 300,000 patient admissions to determine that the expansion was associated with a 7.5 percentage point decrease in the probability of patients being uninsured, a 1.8 percentage point increase in the probability of early uncomplicated presentation, and a 2.6 percentage point increase in the probability of receiving optimal management.

With a variety of data sources, including credit bureaus, the CPS, and government agencies, researchers have found a link between Medicaid Expansion and financial stability. Using over 5 million credit records, Brevoort et al. [2017] finds that the expansion reduced unpaid medical bills sent to collection agencies, prevented new delinquencies, and improved credit scores. Using different data, Hu et al. [2016] also determines that the expansion reduced the number of unpaid bills and the amount of debt sent to collection agencies. Two other papers note even broader impacts on financial stability. Caswell and Waidmann [2017] finds that the expansion improved credit scores, reduced balances past due, reduced the probability of high medical collection balances, reduced the probability of recent medical bills going to collection, and reduced the probability of a new bankruptcy filing. Lee [2017] estimates that households in expansion states with no dependent children and with incomes less than 100% of the FPL had an increased annual dividend income and relied less on financial aid from relatives and friends.

3 Data

I rely on several data sources for this paper: SAHIE, the Kaiser Family Foundation, the ACS, The Bureau of Labor Statistics, and the Eviction Lab.

3.1 Health Insurance Data

I rely on SAHIE data to provide estimates on health insurance rates by county. For the years 2005 to 2007, SAHIE based its estimates on the Annual Social and Economic Supplement to the Current Population Survey (CPS ASEC). For these years, SAHIE calculates estimations for health insurance coverage across four age categories: 0-64, 18-64, 40-64, and 50-64. In addition, SAHIE calculates estimates in health insurance coverage across three income categories: all incomes, 0-200% FPL, and 0-250% FPL.

For years 2008 to 2015, SAHIE models health insurance coverage by combining survey data from the ACS and the 2010 Census with data from demographic population estimates, aggregated federal tax returns, participation records for the Supplemental Nutrition Assistance Program, Community Business Programs, Medicaid, and CHIP records. SAHIE calculates estimations for health insurance coverage across five age categories: 0-64, 18-64, 21-64, 40-64, and 50-64. Moreover, the estimations include six income categories: all incomes, 0-138% FPL, 0-200% FPL, 0-250% FPL, 0-400% FPL, and 138-400% FPL.

SAHIE's use of different datasets after 2007 make comparisons between 2005-2007 data and 2008-2015 data challenging. SAHIE uses the CPS ASEC survey to define a person's "insured" status as being covered "SOME TIME" during the past calendar year. On the other hand, SAHIE relies on the ACS questions "Is this person CURRENTLY covered by [specific type of] health insurance or health coverage plans?" to define insured status.

To extend the SAHIE dataset to 2016, I assume that the ratio between a county's 2015 health insurance rate to its state's 2015 health insurance rate remains constant. I obtain 2016 state-level health insurance estimates from the Census's "Health Insurance Coverage in the United States: 2016" report filed in September 2016. Using the 2015 SAHIE data, I calculate a county-to-state insured rate ratio for each county. I then estimate health insurance coverages for each county in 2016 by using this ratio and the reported Census 2016 state-level health insurance coverage. This methodology relies on the assumption that no significant changes occur in the relationship between health care coverage trends across counties within states. However, this assumption still accounts for significant state-level changes to health insurance coverage. For example, Montana, which expanded Medicaid in January of 2016, saw a dramatic decrease in its rate of uninsured from 11.6 percent in 2015 to 8.1 percent in 2016. My 2016 estimates account for this state-level shift as all counties are assumed to have the same proportional decrease.

In my main regression specifications, I use a SAHIE dataset with uninsured rates for people of all incomes from years 2005-2016. As a robustness check, I run several of my regressions with a SAHIE dataset of uninsured rates for people with incomes under 400% FPL. This income group represents those who would be eligible for Medicaid in expansion states. SAHIE data on this income group only exists from 2008 to 2015, but I extend the dataset to 2016. The lack of data from

2005 to 2007 leads to an omission of eviction data in these years for this regression analysis robustness check.

3.2 Medicaid Expansion Status

I rely on data from the Kaiser Family Foundation for information on which states expanded Medicaid and when these states expanded. The expansion status of each state by the end of 2017 is illustrated in Figure 2. Table 1 lists the expansion status of states along with the dates of expansion and whether a state expanded with a Section 1115 Waiver.

As states expanded at different times, I vary the coding of treatment years in my analysis. In my treatment variable, any given state that has not expanded Medicaid in the given year is coded as "0." So, all states are coded as "0" before 2014. If a state has expanded Medicaid for the full duration of a given year, I code that year as "1" in my treatment variable. Therefore, for expansion states that implemented Medicaid expansion beginning in January 2014, I code 2014 through 2016 as treatment years. A handful of states expanded Medicaid in the middle of the year. I aim to estimate the impact of this partial treatment. For Michigan, which expanded in April 2014, I code the treatment variable as "3/4" in 2014, as the state experienced treatment for three-fourths of the year. I follow a similar methodology for New Hampshire, which expanded in August 2014; Indiana, which expanded in February 2015; Alaska, which expanded in September 2015, and Louisiana, which expanded in July 2016. I code following this method because the more recent SAHIE data relies on the survey question "Is this person CURRENTLY covered by [specific type of] health insurance or health coverage plans?"

For someone at 130% for the FPL in Michigan, that answer could be different in early 2014 or late 2014 because of the implementation date.

Some other Medicaid expansion literature codes "early expanders" differently. Beginning in April 2010, the ACA provided states with the option to get an early start on Medicaid expansion with federal funds. California, Connecticut, the District of Columbia, Minnesota, New Jersey, and Washington all began shifting their state-run healthcare programs to prepare for Medicaid expansion in 2014. However, I choose not to code this early expansion as a full Medicaid expansion treatment because these states often were shifting already insured people from other insurance plans to Medicaid and these early programs failed to cover as much of the states' population as fully implemented Medicaid expansion has.

3.3 Economic and Demographic Data

I rely on data from the ACS 5-Year Estimates and the 2010 Census for calculating eviction rates and for control variables in my regression analysis. The Census Bureau sends the ACS survey to nearly three million households each year, resulting in nearly two million final survey responses. The ACS 5-Year Estimates, which include 60 months of data, are the most reliable ACS estimate, and utilize the largest sample size. I rely on 5-year estimates, as they include county-level estimates.

I use the ACS 5-Year Estimates for a number of demographic and economic control variables in my regression analysis. In these controls, I utilize 5-Year Estimates to provide data for their endpoint year. For example, I use the 2011-2015 Estimates as a measure for 2015 data. I use 2002-2007 Estimates for all 2005-

2007, as 5-year estimates did not exist for earlier years. While this methodology fails to provide precise estimates on these control variables, time and location fixed effects used in regression analysis minimize some of the error.

To control for changes in a county's demographics, I rely solely on the ACS 5-Year Estimates. I include county-level measures of the average household size, the percent female, a series of binary variables indicating race, and a series of binary variables indicating educational attainment. I control for household size and gender because households with children and single-mother household face higher levels of eviction [Desmond et al., 2013; Desmond, 2016]. African-American women in particular face a disproportionate amount of eviction, so I control for race [Desmond, 2016]. I include educational attainment as another standard demographic control.

For economic control variables, I use county-level statistics on the unemployment rate, the median gross household income, the median gross rent, and the median gross rent as a percent of income. I obtain data on the unemployment rate from the Bureau of Labor Statistics. I obtain the other economic control variables from the ACS 5-Year estimates. I choose to include median household income, rent costs, and rent as a percent of income as existing literature points to rent burden as a cause of eviction [Desmond, 2012].

3.4 Evictions

To measure county-level evictions, I rely on data from The Eviction Lab. The Eviction Lab obtained these data from an agreement with the vendor LexisNexis. Through a variety of methods, LexisNexis obtained individual eviction court filings from across the country. I aggregate the number of court-processed evictions to the county level in each given year to obtain a measure of the total number of formal evictions in that county.

Unless otherwise specified, I use all available eviction data from 2005 to 2016. However, there are some states in which I drop data for specific years or from the whole dataset for my regression analysis. I drop these data because of variations in data collection across time within a given location. In my regression analysis, I omit data from 2005 in the District of Columbia, from 2005-2007 in Maine, from 2014-2016 in New Hampshire, from 2008-2016 in New York, from 2005-2007 and 2013-2014 in Rhode Island, from 2005-2007 and 2009 in South Carolina, from 2005 and 2016 in New Jersey, from 2005-2006 in West Virginia, from 2005-2007 in Massachusetts, and all data from Pennsylvania. I keep these data in summary statistics tables and figures in Appendix A, which provides raw data.

In my regression analysis, I include localities with consistent undercounts as geographic fixed effects account for consistent low estimates. In my main DD regression specifications, I have eviction data for 2,735 counties, or about 87% of the country. In another specification, I omit unbalanced observations, or those counties that lack data across 2005-2016, and, consequently, I use eviction data for 1,540 counties, nearly 50% of the country.

4 Empirical Approaches

I follow similar methodologies to Duggan et al. [2017] and Courtemanche et al. [2016] that examine the impact of Medicaid expansion across outcomes. I begin by using a DD model to isolate the impact of the expansions on eviction rates. I then repeat my DD model restricting my sample to CZs stretching across multiple states that have variation in expansion implementation. Next, I use a DDD model to include variation in the expansion's treatment intensity. Using the triple difference term in the DDD model, I attempt an IV model to estimate the broader relationship between health insurance and eviction rates. Lastly in Appendix B, I attempt a synthetic control model, as in Abadie et al. [2010], as a robustness check to my standard regression analyses. Throughout my analyses, my demographic control variables at the county-level include average household size, percent of the population female, dummy variables for race, and dummy variables for educational attainment. My economic control variables at the county-level include unemployment rate, median household income, median gross rent, and median rent as percent of income.

4.1 Difference-in-Differences Model

I use a DD equation to estimate the causal impact of Medicaid expansion on eviction rates. Through a series of controls, fixed effects, and linear time trends, I am able to isolate the impact of the expansion on eviction rates. My preferred specification is as follows:

$$Eviction_{cst} = \beta_0 + \beta_1(Medicaid_s * Post_{st}) + \beta_2\chi_{cst} + \beta_3\lambda_{cst} + \gamma_t + \alpha_{cs} + \sigma_c * t + \epsilon_{cst} \quad (1)$$

where $Eviction_{cst}$ is the eviction rate in county c, state s, and year t; $Medicaid_s$ is a dummy variable indicating whether state s expanded Medicaid; $Post_{st}$ indicates whether state s had expanded Medicaid in year t; χ_{cst} is a vector of demographic controls in county c, state s, and in year t; λ_{cst} is a vector of economic controls in county c, state s, and in year t; γ_t is a time fixed effect for year t; α_{cs} is a geographic fixed effect for county c in state s; $\sigma_c * t$ is an interaction term between the county fixed effects and a linear time trend; and ϵ_{cst} is an heteroskedastic robust-error term clustered at the state level. I also run this regression varying my fixed effects and linear time trends. I vary the inclusion of interacted county and year fixed effects as well as the inclusion of Census division or Census region linear time trends.

In equation (1), β_2 has a causal interpretation as Medicaid expansion's impact on county-level eviction rates. This relies on the DD identifying assumption that conditional on other covariates, changes in post-expansion year eviction rates would have been the same in expansion and non-expansion states without the ACA. To further assert the causality of my estimate, I include trends in several other factors for expansion and non-expansion states. In Figures 3 - 9, I include trends in rent as a percent of income, median gross rent, the unemployment rate, median household income, health insurance coverage, and eviction rates. I include these measures because existing literature, as noted, points to these factors as causes of eviction. In these trends, I code states' treatment year as the year they expanded Medicaid if the expansion was implemented before July of that year. If the expansion was implemented in July or later, I code the treatment year as the following year. In these figures, non-expansion states have time from treatment as zero in 2014.

4.2 Difference-in-Differences Border County Model

Another method I try mirrors that of Yagan [2017], which utilizes interstate intra-CZ policy differences. This approach, in theory, enables me to take advantage of variation in Medicaid expansion implementation across similar labor markets. I run a similar DD model as in equation (1); however, I limit my sample size to CZs that stretch across multiple states, in which at least one is a non-expansion state and one is an expansion state. I am able to then compare counties that border each other but have different expansion statues. Figure 10 illustrates which CZs have such policy variation. My equation for this model is as follows:

$$Eviction_{cst} = \beta_0 + \beta_1(Medicaid_s * Post_{st}) + \beta_2\chi_{cst} + \beta_3\lambda_{cst} + \gamma_t + \alpha_{cs} + \tau_{zt} + \epsilon_{cst} \quad (2)$$

where all terms are the same as in Equation (1) except τ_{zt}, which is an interaction of CZ and year fixed effects.

My data for this model include 43 CZs and 221 counties. When I further limit the data to CZs that stretch across only two states, my data include 38 CZs and 185 counties. I include a restriction of CZs that include only two states with the hypothesis that commuting zones across three states could have inherent differences from those that stretch across two states. For example, having similar labor market conditions across three states could make individuals more likely to move states in order to align with local policy preferences than if labor market conditions were only similar across two states. The Metropolitan Areas dropped when I restrict the sample to two-state CZs are Bethesda-Frederick-Gaithersburg, Burlington, Keokuk-Fort Madison, Lexington Park, Memphis, Sioux City, Texarkana, and

Washington-Arlington-Alexandria.

4.3 Difference-in-Difference-in-Differences Model

I use a DDD model to incorporate the treatment intensity of Medicaid expansion in each county. This method also enables me to better examine other portions of the ACA's reform, such as subsidies; however, I focus on expansion as it likely better targets populations prone to eviction. The DDD model assumes that a county's treatment is proportional to its baseline uninsured rate. My preferred specification is as follows:

$$\begin{aligned} Eviction_{cst} = &\beta_0 + \beta_1(Medicaid_s * Post_{st} * Uninsured_{cs}) + \beta_2(Post_{st} * Uninsured_{cs}) \\ &+ \beta_3\chi_{cst} + \beta_4\lambda_{cst} + \gamma_t + \alpha_{cs} + \rho_{st} + \sigma_c * t + \epsilon_{cst} \end{aligned} \tag{3}$$

where all the terms are the same as in Equation (1) except ρ_{st}, which is an interaction of state and year fixed effects.

The effect of the Medicaid expansion on eviction rates is given by $\beta_1 * Uninsured$. I omit a $Medicaid * Post$ interaction term as it is absorbed by the interacted state and year fixed effects. My identification strategy assumes that, conditional on covariates, areas with low baseline uninsured rates and areas with high baseline uninsured rates would have changed in similar ways without the ACA. In addition, I assume that expansion states' and non-expansion states' share of uninsured individuals under 400% of the FPL would have changed in similar ways without the ACA. Effects from the subsidies and other non-expansion provisions of the ACA are given by $\beta_2 * Uninsured$. This term is expected to be larger for non-expansion states as individuals between 100% and 138% of the FPL would be eligible for subsidies instead of Medicaid. Moreover, it is unclear if there were changes from private to public insurance coverage; however, that proves irrelevant for my analysis.

4.4 Instrumental Variable Model

Using a similar equation to my DDD model, I attempt to estimate the elasticity of health insurance and eviction rates using an IV model. In the first-stage equation, I use my preferred DDD specification; however, I change the outcome variable to the post-treatment uninsured rate. In the second stage equation, I regress eviction rates on the predicted value of uninsured rates obtained from the first stage equation. My original DDD model serves as a reduced form equation. The first and second stage equations are as follows:

First-stage equation:

$$\begin{aligned} Uninsured_{cst} = &\pi_0 + \pi_1(Medicaid_s * Post_{st} * Uninsured_{cs}) + \pi_2(Post_{st} * Uninsured_{cs}) \\ &+ \pi_3\chi_{cst} + \pi_4\lambda_{cst} + \gamma_t + \alpha_{cs} + \rho_{st} + \sigma_c * t + \epsilon_{cst} \end{aligned} \tag{4}$$

Structural equation:

$$Eviction_{cst} = \beta_0 + \beta_1 Unin\hat{s}ured_{cst} + \beta_2\chi_{cst} + \beta_3\lambda_{cst} + \gamma_t + \alpha_{cs} + \rho_{st} + \sigma_c * t + \epsilon_{cst} \tag{5}$$

where all the terms are as defined in Equation (3).

The F-statistics in Table 15 show that the instrumental variables are strong when using either just the triple interaction term or both the triple interaction term and the *Post*Uninsured* interaction term. However, these instruments could violate the exclusion restriction. One could argue that the ACA impacted eviction rates in ways other than an individual's obtaining health insurance. For example, the reform changed insurance coverage, payment structures, and plans' generosity. These factors could also have impacted eviction rates. For example, if a plan became more generous an individual may have been able to seek treatment that would enable her to stay at work and thus pay off rent.

5 Results

Table 3 displays results from my DD model in Equation (1) as well as other specifications of the equation varying the inclusion of interacted geographic and year time fixed effects and of county linear time trends. The first three columns omit county linear time trends and vary in their inclusion of interacted Census region time fixed effects or Census division region time fixed effects. The next three columns include county linear time trends and also vary in their inclusions of the interacted terms. Column (4) is my preferred specification, which omits interacted geographic and time fixed effects. All of the specifications include demographic controls for county-level race, gender, education level, and average household size; economic controls for county-level median household income, gross median rent, rent as a percent of income, and unemployment rate; year fixed effects; and county fixed effects. The table also includes the mean eviction rate for the sample used and the coefficient on *Medicaid*Post* as a percent of the mean eviction rate.

The results in Table 3 suggest that the Medicaid expansion had a negative impact on eviction rates. In my preferred specification, the expansion is associated with a 12.5% decrease in eviction rates or about 1 fewer eviction per 400 renting households. The 95% confidence interval on this estimate ranges from -25.7% to 0.7%. Without county linear time trends, in Columns (1) - (3) the estimate ranges from 4.8% to 8.3%. With interacted geographic and time fixed effects and county linear time trends in Columns (5) and (6) the estimate ranges from 8.6% to 11.2%. The consistent negative estimate across specifications suggests a negative relationship between Medicaid expansion and eviction rates; however, I cannot rule out that the Medicaid expansion had no effect as the 95% confidence intervals includes 0. The majority of the sample only has two post-treatment years of data and states that expanded after 2014 have even less post-treatment data. This data limitation likely increases the standard errors.

Tables 4 - 7 include results of the DD model repeated across a variety of other specifications. In these tables, I only include my preferred DD; however, when varying the inclusion of interacted geographic and time fixed effects and of county linear time trends the direction of the estimates remain constant, as in Table 3. In Table 4 Column (1), I restrict the sample only to counties that have data in every year from 2005-2016, thereby using only about half of the dataset. In Column (2), I use county-level uninsured rates only for the population under 400% of the FPL and can only include data from 2008-2016 because of limited insurance data. In Column (3), I drop states that expanded in the middle of a year and Massachusetts because of its extensive pre-ACA healthcare reform. In Table 5, Column (1) includes data only from counties in the top quartile of pre-treatment median rent as a percent of income whereas Column (2) is the bottom quartile. Table 6 does the same but instead divides the counties by pre-treatment total population and also includes a regression using the middle quartiles. In Table 6, I divide my sample into urban and non-urban counties. Using the National Center of Health Statistics classifications, I define urban counties as those that are "large central metro," "large fringe metro," and "medium metro." Non-urban counties are those that are "small metro," "micropolitan," and "non-core." Column (1) includes only urban counties and Column (2) includes only non-urban counties.

The results from the specifications in Tables 4 - 7 all maintain the negative estimate on the impact of Medicaid expansion on eviction rates and also reveal heterogeneity in the impact of the expansion on eviction rates. Table 4 shows that Medicaid expansion is associated with an 18.7% decrease in eviction rates in the counties with the highest rent as percent of income. The 95% confidence interval on this estimate ranges from -42.7% to 5.2%. In these rent-burdened counties, in which the average pre-treatment rent as a percent of income was nearly 33%, I estimate the Medicaid expansion led to nearly one fewer eviction per 200 renting households. On the other hand, in the least rent-burdened counties where the average pre-treatment rent as a percent of income was 23.6% , I estimate only a 1.4% decrease in the eviction rate. These results follow existing literature and suggest that those with the greatest rent burden may have benefited the most from Medicaid expansion in terms of maintaining housing stability.

Next, I explore whether the Medicaid expansion may have had a larger impact on counties based on other characteristics. Table 6 includes the results of the DD model when the sample is broken up into quartiles by total population. Intuitively, one may expect the Medicaid expansion to have a larger effect in counties with a greater population that include a larger renting community and more economic growth. Column (1) indicates that the coefficient on this regression for the counties in the top quartile of total population is a smaller fraction of the mean eviction rate than it is when using the whole dataset. As expected, in Column (3) the coefficient as a percent of the dependent variable is just over half of that of Column (1). One would expect small population counties to have less pressure in the rental market and perhaps more personal relationships between landlord and tenants. Surprisingly, Column (2) indicates that the coefficient as a percent of the mean for the middle two quartiles of counties is 15.7%. It is unclear why these counties would experience a larger effect, but one could posit that a less tight rental market and easier logistics in implementing government programs may play a role.

Similarly, I examine the sample when restricting it to either urban or non-urban counties. Using the National Center for Health Statistics classifications, my defined urban counties are all part of metropolitan statistical areas (MSAs) of over 250,000 people. Non-urban counties are in smaller MSAs or are not in MSAs. Table 7 shows these results. In urban counties Medicaid expansion is associated with a reduction of 0.37 evictions per 100 renting households whereas in non-urban counties it is associated with a reduction of 0.21 evictions per 100 renting households. Perhaps counterintuitively, the reduction as percent of the mean eviction rate in these counties is greater in non-urban counties. Although evictions are more prevalent in urban counties, the Medicaid expansion could have a larger relative effect in non-urban counties because more renters are at the margin of non-payment of rent or because of more flexible landlord tenant relationships. Fundamental differences in urban and non-urban eviction are not yet clear.

Another possible source of heterogeneity in the impact of the expansion is regional variation. If renting, eviction, or health insurance conditions are significantly different across the country's regions, one could expect the Medicaid expansion to have a heterogeneous impact on eviction rates across these regions. Trying to isolate for regional differences is challenging using the DD model because there is little heterogeneity in Medicaid expansion implementation within regions. For example, in the Northeast, Maine is the only state that has yet to implement Medicaid expansion, so it would be the only control group in this area.

Restricting my sample to CZs that stretch across multiple states, which have variation in expansion status, further reveals heterogeneity. Table 8 includes the results of the DD model using data from 43 commuting zones. Columns (1) - (3) vary in their inclusion of economic and demographic controls and my preferred specification, Column (4), uses both sets of controls. Using this methodology, the impact of the expansion appears substantially smaller than when running the DD regression over the whole dataset. Using my preferred specification, the Medicaid expansion is associated with a 3.2% reduction in the mean eviction rate. Table 9 summarizes pre-treatment averages for expansion and non-expansion counties in this sample. Of note, expansion states have a lower initial uninsured and eviction rate, a lower unemployment rate, a more educated population, and a marginally higher median rent as percent of income. These statistics are similar to those of the whole sample's expansion and non-expansion state as depicted in Figures 3 - 9.

Eliminating CZs that stretch across three states from the analysis has a substantial impact on the results. As seen in Table 10, after removing the five CZs that stretched across three states, the point estimates are larger and gain statistical significance. In my preferred specification, the expansion is associated with an 11.6% reduction in eviction rates. Although the estimate is significant at the 10% level, I am still unable to rule out that Medicaid expansion had no impact on these counties' eviction rates as the 95% confidence interval on the estimate ranges from -24.1% to 0.8%. Table 11 shows the pre-treatment averages for this sample. As compared to including the tri-state CZs, the expansion and non-expansion counties now have a more similar pre-treatment eviction rate and uninsured rate. The expansion counties are also slightly more rent-burdened. The causal impact of Medicaid expansion in the sample excluding tri-state CZs is furthered by a non-parametric regression robustness check illustrated in Figure 12b. It is unclear what attributes the five tri-state CZs have that shift the results both in magnitude and in significance. Nevertheless, the changed result is illustrative of the heterogeneity of the impact of the Medicaid expansion.

One source of potential heterogeneity is county's pre-treatment uninsured rates. Using the DDD model I explore whether Medicaid expansion's treatment intensity affects its impact on eviction rates. Table 12 includes results from my DDD model across a variety of specifications. In Columns (1) - (3), I vary the inclusion of the same demographic and economic controls I used in the DD model and I also omit county linear time trends. In Columns (4) - (6), I vary the inclusion of the controls and use county linear time trends. Column (6) is my preferred specification which includes all controls.

Without the county linear time trends, the coefficients in Columns (1) - (3) on the triple interaction term suggest that the expansion increased the eviction rate and that counties with a higher baseline uninsured rate would have a larger increased eviction rate. Including the county linear time trends flips these results. In Columns (4) - (6) the coefficient is negative, suggesting that the expansion decreased eviction rates and had a larger impact in counties with higher initial uninsured rates. However, across each specification the coefficient is far smaller in magnitude than those from the DD model suggesting that the baseline uninsured rate is negligible in the expansion's impact on eviction rates. With the point estimates small in magnitude and near zero, I rule out that the baseline uninsured rate of a county has a substantial impact on the expansion's effect on eviction rates. As with the DD model, I run my DDD preferred specification separately weighting by total population, with balanced data, when dropped mid-year expanders and Massachusetts, when using the <400% of FPL uninsured rate, and when including the top quartile of rent burdened counties. The results did not change in significance or direction. Results of these robustness checks are in Table 13. If there were significant classical measurement error in the SAHIE insurance rate estimates, the coefficients across the DDD specifications could be biased toward zero. This error would be further exacerbated by my inclusion of controls.

In my IV model, I find that gains in insurance coverage are associated with an increase in the eviction rate. Table 14 includes my first-stage regression results varying the inclusion of county-linear time trends. Column (2) is my preferred specification, which uses the time trends. As expected, in expansion states, a higher baseline uninsured rate leads to a greater impact of the Medicaid expansion on post-treatment insurance rates. Moreover, the ACA implementation led to decreases in the uninsured rate. Table 15 shows the results from my second-stage equation. In Column (1), my preferred specification, I use two instruments whereas in Column (2) I use only the triple interaction term as an instrument. I estimate that a one percentage point decrease in the uninsured rate leads to a rise of 0.065 evictions per 100 renting households. However, as discussed earlier, there is reason to be skeptical about this estimate given other ways through which the ACA could have impacted eviction rates other than an individual gaining insurance. Moreover, in both specifications, the estimate is statistically insignificant as is the case with the reduced form DDD equation.

6 Conclusion and Policy Implications

The early evidence presented in this paper suggests that the Medicaid expansion lowered county-level eviction rates. Using a novel dataset, I find consistent estimates across robustness checks and regression specifications that show this relationship. Although the size of the standard errors prevent me from ruling out no relationship, this early evidence is promising considering there are only two post-treatment years of data. Moreover, the magnitude of this finding in terms of a reduced eviction count could be made larger with a comprehensive dataset.

Counter to much of the existing Medicaid expansion literature, the baseline county-level uninsured rate does not seem to matter for the expansion's impact on eviction rates. This could be explained by counties coupling the expansion with other reforms. For example, if expansion counties all reformed their healthcare administration or decided to revamp health centers as part of the reform, that could explain why expansion might improve conditions beyond just a more insured population. Future literature could try to disentangle reforms associated with Medicaid expansion to see if they had a causal impact on other welfare outcomes like housing stability.

Future literature should also try to understand the evident heterogeneity in the impact of expansion across different kinds of counties. I estimate that the expansion had a larger impact on rent-burdened counties, and there are likely other important sources of variation. Parsing through these nuances will help policymakers understand the relationship between county-level health insurance and housing stability. In one county, eviction could be predominantly an income problem in which the labor market is preventing renters from meeting payments. In this case, health care could be an important factor in improving the labor force. In another county, eviction could be caused by rapidly rising rent costs. Health insurance in such a county could help a family smooth payments and better financially prepare for the housing market. Knowing the nuances of these relationships will unveil important broader economic conditions.

For federal policymakers, this paper adds a new layer to the cost-benefit analysis of the ACA and other healthcare reforms. The aim of Medicaid expansion was to improve welfare for low-income individuals. If the expansion not only gives these individuals the proven benefits of access to care, but also leads to greater housing stability, policymakers should aim to further expand health insurance. In addition, the costs of such reforms can be better justified if increasing funds for Medicaid reduces the need for additional money in federal housing programs. A theoretical way to consider this question would be to examine an optimal health benefit rate model similar to Baily [1978] and Chetty [2005]. If health insurance coverage has a negative elasticity with eviction rates, as my results suggest, the optimal health insurance benefit rate should be higher than previously assumed.

I alter existing models to theorize a model using this elasticity in Appendix C.

For governors in states that have yet to expand Medicaid, this finding should add to their considerations. When deciding between expanding and not expanding, governors should consider the broader economics of implementing an expanded Medicaid. The impacts of health insurance and Medicaid, in particular, are well known. But if expanding leads to fewer people losing their homes, there are second order consequences that are important. Children, adults, and families will fare better with housing stability. Moreover, neighborhoods, landlords, and others will benefit as well. Financially, too, as the federal government covers most of the cost of Medicaid expansions, if these reforms can improve individuals' lives beyond healthcare, it could reduce the need for states and localities to spend on welfare programs.

A dollar spent on healthcare has spillover effects on housing, on education, and on broader community welfare. The challenges of providing general welfare are interconnected. Therefore, when considering welfare policy, the solutions should be, too. If society aims to end material deprivation poverty, ensuring that each individual has access to food, education, healthcare, and housing, we must do a better job understanding the nuanced connections between these issues. Moreover, we must understand their causes and consequences. Housing instability has roots in stagnating incomes, rising rents, and prior discriminatory housing policy. Tackling all of these causes necessitates more than just housing policy reform. Providing healthcare is such a solution.

7 Tables

Table 1: Medicaid Expansion Status by State

State	Expanded by January 2018?	Expansion Details
Alabama	No	-
Alaska	Yes	Expanded September 2015
Arizona	Yes	Expanded January 2014 with Section 1115 Waiver
Arkansas	Yes	Expanded January 2014 with Section 1115 Waiver
California	Yes	Expanded January 2014
Colorado	Yes	Expanded January 2014
Connecticut	Yes	Expanded January 2014
Delaware	Yes	Expanded January 2014
District of Columbia	Yes	Expanded January 2014
Florida	No	-
Georgia	No	-
Hawaii	Yes	Expanded January 2014
Idaho	No	-
Illinois	Yes	Expanded January 2014
Indiana	Yes	Expanded February 2015 with Section 1115 Waiver
Iowa	Yes	Expanded January 2014 with Section 1115 Waiver
Kansas	No	-
Kentucky	Yes	Expanded January 2014
Louisiana	Yes	Expanded July 2016
Maine	No	Expansion passed ballot initiative in November 2017
Maryland	Yes	Expanded January 2014
Massachusetts	Yes	Expanded January 2014
Michigan	Yes	Expanded January 2014 with Section 1115 Waiver
Minnesota	Yes	Expanded January 2014
Mississippi	No	-
Missouri	No	-
Montana	Yes	Expanded January 2016 with Section 1115 Waiver
Nebraska	No	-
Nevada	Yes	Expanded January 2014
New Hampshire	Yes	Expanded January 2014 with Section 1115 Waiver
New Jersey	Yes	Expanded January 2014
New Mexico	Yes	Expanded January 2014
New York	Yes	Expanded January 2014
North Carolina	No	-
North Dakota	Yes	Expanded January 2014
Ohio	Yes	Expanded January 2014
Oklahoma	No	-
Oregon	Yes	Expanded January 2014
Pennsylvania	Yes	Expanded January 2015
Rhode Island	Yes	Expanded January 2014
South Carolina	No	-
South Dakota	No	-
Tennessee	No	-
Texas	No	-
Utah	No	-
Vermont	Yes	Expanded January 2014
Virginia	No	-
Washington	Yes	Expanded January 2014
West Virginia	Yes	Expanded January 2014
Wisconsin	No	All adults up to 100% FPL covered
Wyoming	No	-

Source: Kaiser Family Foundation

Table 2: Medicaid Expansion Literature Meta-Analysis

	Empirical Approach	Effect of Medicaid Expansion
Insurance Coverage		
Duggan et al. [2017]	DD, DDD	Insurance gains due to the ACA were over 50% larger in expansion states
Frean et al. [2017]	DDD	The full ACA increased proportion of insured people by nearly double in expansion states
Courtemanche et al. [2016]	DDD	Medicaid accounted for 60% of ACA coverage gains
Labor Market		
Duggan et al. [2017]	DD, DDD	Relatively small aggregate labor market impact on both the extensive and intensive margin, likely heterogeneous effect
Slusky and Ginther [2017]	DD	Decreased the prevalence of divorce among college educated 50-64 year-olds
Goodman [2017]	DD	No migration effect that would meaningfully increase the number of enrollees in expansion states
Leung and Mas [2016]	DD	No employment lock among childless adults who were previously ineligible for coverage
Kaestner et al. [2015]	DD, Synth	Statistically insignificant positive impact on work effort
Gooptu et al. [2016]	DD	No significant changes in employment, job switching, or full- versus part-time employment in 15 months following expansion
Frisvold and Jung [2017]	DD	No impact on labor force participation, employment, and hours worked
Health Outcomes		
Maclean et al. [2017]	DD	Increased Medicaid financed smoking cessation prescriptions and total payments
Maclean and Saloner [2017]	DD	Increased prescriptions for medication treating substance use disorders
Ghosh et al. [2017]	DD	Medicaid-financed prescription utilization increased
Dranove et al. [2016]	DD	Decreased the costs of uncompensated care
Simon et al. [2017]	DD	Increased the use of certain forms of preventative care and modestly improved self-reported health
Courtemanche et al. [2017a]	DDD	Slowed ambulance response times and added a strain to emergency response systems
Courtemanche et al. [2017b]	DDD	Some evidence that in expansion states the ACA improved self-assessed health among older non-elderly adults
Nikpay et al. [2017]	DD	Increased the use of emergency department visits
Loehrer et al. [2018]	DD	In patient admissions, increased probability of uncomplicated presentation and or receiving optimal care
Financial Stability		
Brevoort et al. [2017]	DD	Reduced unpaid medical bills, prevented new delinquencies, and improved credit scores
Hu et al. [2016]	Synth	Reduced unpaid bills and debt sent to collection agencies in zip codes with most pre-expansion number of uninsured & low-income
Caswell and Waidmann [2017]	DDD	Reduced balances past due as % of debt, reduced probability of large medical collection balance, reduced probability of new bankruptcy filing, etc.
Lee [2017]	DD	Increased dividend income and decreased familial family assistance for households <100% FPL with no children

Table 3: Difference-in-Difference Regression Results

VARIABLES	(1) Eviction Rate	(2) Eviction Rate	(3) Eviction Rate	(4) Eviction Rate	(5) Eviction Rate	(6) Eviction Rate
Medicaid*Post	-0.168	-0.0984	-0.106	-0.254	-0.228	-0.181
	(0.168)	(0.157)	(0.126)	(0.137)	(0.156)	(0.158)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Economic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Census Region FE X Year FE	No	Yes	No	No	Yes	No
Census Division FE X Year FE	No	No	Yes	No	No	Yes
County Linear Time Trends	No	No	No	Yes	Yes	Yes
Mean Eviction Rate	2.03	2.03	2.03	2.03	2.03	2.03
Coefficient as % of Mean	8.3%	4.8%	5.2%	12.5%	11.2%	8.6%
Number of States (inc. D.C.)	48	48	48	48	48	48
Number of Counties	2,735	2,735	2,735	2,735	2,735	2,735
Observations	27,946	27,946	27,946	27,946	27,946	27,946

Notes: Eviction rate is measured as the number of evictions per 100 renting households. Regressions exclude singleton observations. Eviction data from states with varying levels of data collection across time are excluded. These dropped data are from Washington D.C. in 2005, Maine in 2005-2006, New Hampshire in 2015-2016, New York in 2007-2016, Rhode Island in 2005-2007 and 2013-2014, South Carolina in 2005-2008 and 2016, New Jersey in 2005 and 2016, West Virginia in 2005-2006, Massachusetts in 2005-2007, and all Pennsylvania data. Robust standard errors are clustered at states and are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Sources: The Eviction Lab, Census Small Area Health Estimates, Census American Community Survey 5-Year Estimates, 2010 Census

Table 4: Difference-in-Difference Regression Results Robustness Checks

	(1)	(2)	(3)
	Balanced Data	*Under 400 % FPL Uninsured*	*Dropping States*
VARIABLES	Eviction Rate	Eviction Rate	Eviction Rate
Medicaid*Post	-0.347	-0.180	-0.151
	(0.235)	(0.145)	(0.132)
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Economic Controls	Yes	Yes	Yes
Census Region FE X Year FE	No	No	No
Census Division FE X Year FE	No	No	No
County Linear Time Trends	Yes	Yes	Yes
Mean Eviction Rate	2.47	1.99	1.93
Coefficient as % of Mean	14.0%	9.0%	7.8%
Number of States (inc. D.C.)	38	47	42
Number of Counties	1,540	2,665	2,494
Observations	18,476	21,173	25,353

Notes: Column (1) excludes any county for which eviction data is missing in any year from 2005 to 2016. Column (2) uses uninsured rates are estimated for people with incomes <400% of the Federal Poverty Line. Health insurance data for this income group are only available starting in 2008. Column (3) excludes data from Michigan, New Hampshire, Indiana, Alaska, Louisiana, and Massachusetts. Regressions exclude singleton observations. Eviction data from states with varying levels of data collection across time are excluded. These dropped data are from Washington D.C. in 2005, Maine in 2005-2006, New Hampshire in 2015-2016, New York in 2007-2016, Rhode Island in 2005-2007 and 2013-2014, South Carolina in 2005-2008 and 2016, New Jersey in 2005 and 2016, West Virginia in 2005-2006, Massachusetts in 2005-2007, and all Pennsylvania data. Eviction rate is measured as the number of evictions per 100 renting households. Robust standard errors are clustered at states and are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Sources: The Eviction Lab, Census Small Area Health Insurance Estimates, Census American Community Survey 5-Year Estimates, 2010 Census

Table 5: Difference-in-Difference Regression Results – By Rent as Percent of Income

VARIABLES	(1) *Top 25%* Eviction Rate	(2) *Bottom 25%* Eviction Rate
Medicaid*Post	-0.487	0.0157
	(0.318)	(0.114)
Year FE	Yes	Yes
County FE	Yes	Yes
Demographic Controls	Yes	Yes
Economic Controls	Yes	Yes
Census Region FE X Year FE	No	No
Census Division FE X Year FE	No	No
County Linear Time Trends	Yes	Yes
Mean Eviction Rate	2.60	1.11
Coefficient as % of Mean	18.7%	1.4%
Mean Rent As Percent of Income	32.79%	23.56%
Number of States (inc. D.C.)	44	36
Number of Counties	704	699
Observations	7,040	6,947

Notes: Counties are sorted by their pre-2014 mean median rent as percent of income. Eviction rate is measured as the number of evictions per 100 renting households. Regressions exclude singleton observations. Eviction data from states with varying levels of data collection across time are excluded. These dropped data are from Washington D.C. in 2005, Maine in 2005-2006, New Hampshire in 2015-2016, New York in 2007-2016, Rhode Island in 2005-2007 and 2013-2014, South Carolina in 2005-2008 and 2016, New Jersey in 2005 and 2016, West Virginia in 2005-2006, Massachusetts in 2005-2007, and all Pennsylvania data. Robust standard errors are clustered at states and are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Sources: The Eviction Lab, Census Small Area Health Insurance Estimates, Census American Community Survey 5-Year Estimates, 2010 Census

Table 6: Difference-in-Difference Regression Results – By Population Size

	(1)	(2)	(3)
	Top 25%	*Middle Quartiles*	*Bottom 25%*
VARIABLES	Eviction Rate	Eviction Rate	Eviction Rate
Medicaid*Post	-0.308	-0.296	-0.0516
	(0.258)	(0.192)	(0.126)
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes
Economic Controls	Yes	Yes	Yes
Census Region FE X Year FE	No	No	No
Census Division FE X Year FE	No	No	No
County Linear Time Trends	Yes	Yes	Yes
Mean Eviction Rate	3.28	1.88	1.05
Coefficient as % of Mean	9.4%	15.7%	4.9%
Number of States (inc. D.C.)	48	44	38
Number of Counties	665	1310	760
Observations	7,036	13,953	6,957

Notes: Counties are sorted by their pre-2014 mean population. Eviction rate is measured as the number of evictions per 100 renting households. Regressions exclude singleton observations. Eviction rate is measured as the number of evictions per 100 renting households. Regressions exclude singleton observations. Eviction data from states with varying levels of data collection across time are excluded. These dropped data are from Washington D.C. in 2005, Maine in 2005-2006, New Hampshire in 2015-2016, New York in 2007-2016, Rhode Island in 2005-2007 and 2013-2014, South Carolina in 2005-2008 and 2016, New Jersey in 2005 and 2016, West Virginia in 2005-2006, Massachusetts in 2005-2007, and all Pennsylvania data. Robust standard errors are clustered at states and are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Sources: The Eviction Lab, Census Small Area Health Insurance Estimates, Census American Community Survey 5-Year Estimates, 2010 Census

Table 7: Difference-in-Difference Regression Results – By County Classification

VARIABLES	(1) *Urban* Eviction Rate	(2) *Non-urban* Eviction Rate
Medicaid*Post	-0.370	-0.206
	(0.276)	(0.158)
Year FE	Yes	Yes
County FE	Yes	Yes
Demographic Controls	Yes	Yes
Economic Controls	Yes	Yes
Census Region FE X Year FE	No	No
Census Division FE X Year FE	No	No
County Linear Time Trends	Yes	Yes
Mean Eviction Rate	3.15	1.58
Coefficient as % of Mean	11.7%	13.0%
Number of States (inc. D.C.)	45	46
Number of Counties	739	1,996
Observations	7,950	19,996

Notes: Urban counties includes Large central metro, large fringe metro, and medium metro counties, as defined by National Center for Health Statistics. Non-urban counties includes small metro, micropolitan, and non-core counties. Eviction rate is measured as the number of evictions per 100 renting households. Regressions exclude singleton observations. Eviction data from states with varying levels of data collection across time are excluded. These dropped data are from Washington D.C. in 2005, Maine in 2005-2006, New Hampshire in 2015-2016, New York in 2007-2016, Rhode Island in 2005-2007 and 2013-2014, South Carolina in 2005-2008 and 2016, New Jersey in 2005 and 2016, West Virginia in 2005-2006, Massachusetts in 2005-2007, and all Pennsylvania data. Robust standard errors are clustered at states and are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Sources: The Eviction Lab, Census Small Area Health Insurance Estimates, Census American Community Survey 5-Year Estimates, 2010 Census

Table 8: Border Counties Difference-in-Difference Regression Results

VARIABLES	(1) Eviction Rate	(2) Eviction Rate	(3) Eviction Rate	(4) Eviction Rate
Medicaid*Post	-0.0834	-0.0630	-0.0594	-0.0585
	(0.141)	(0.107)	(0.139)	(0.107)
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Commuting Zone FE * Year FE	Yes	Yes	Yes	Yes
Demographic Controls	No	Yes	No	Yes
Economic Controls	No	No	Yes	Yes
Mean Eviction Rate	1.82	1.82	1.82	1.82
Coefficient as % of Mean	4.6%	3.5%	3.3%	3.2%
Number of States (inc. D.C.)	28	28	28	28
Number of Counties	221	221	221	221
Number of Commuting Zones	43	43	43	43
Observations	2,277	2,277	2,277	2,277

Notes: Eviction rate is measured as the number of evictions per 100 renting households. Regressions exclude singleton observations. Louisiana is not included as an expansion state in 2016. Eviction data from states with varying levels of data collection across time are excluded. These dropped data are from Washington D.C. in 2005, Maine in 2005-2006, New Hampshire in 2015-2016, New York in 2007-2016, Rhode Island in 2005-2007 and 2013-2014, South Carolina in 2005-2008 and 2016, New Jersey in 2005 and 2016, West Virginia in 2005-2006, Massachusetts in 2005-2007, and all Pennsylvania data. Robust standard errors are clustered at states and are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Sources: The Eviction Lab, Census Small Area Health Insurance Estimates, Census American Community Survey 5-Year Estimates, 2010 Census

Table 9: Border Counties Difference-in-Differences 2013 Means

2013 Mean	Non-Expansion	Expansion
Eviction Rate	2.18	1.43
Uninsured Rate	15.25	14.10
Unemployment Rate	7.34	7.06
Median Household Income	$50,689	$53,317
Median Gross Rent	$753	$769
Median Rent as Percent of Income	29.14	29.23
Household Size	2.52	2.54
% Female	50.08%	50.40%
% African-American	9.97%	6.33%
% Less Than HS	14.61%	13.57%
% High School	34.59%	33.12%
% Some College	29.37%	30.22%
% College	13.69%	15.01%
% More Than College	7.73%	8.08%
Counties	98	84

Notes: Eviction rate is measured as the number of evictions per 100 renting households. Regressions exclude singleton observations. Louisiana is not included as an expansion state in 2016. Eviction data from states with varying levels of data collection across time are excluded. These dropped data are from Washington D.C. in 2005, Maine in 2005-2006, New Hampshire in 2015-2016, New York in 2007-2016, Rhode Island in 2005-2007 and 2013-2014, South Carolina in 2005-2008 and 2016, New Jersey in 2005 and 2016, West Virginia in 2005-2006, Massachusetts in 2005-2007, and all Pennsylvania data. Robust standard errors are clustered at states and are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Sources: The Eviction Lab, Census Small Area Health Insurance Estimates, Census American Community Survey 5-Year Estimates, 2010 Census

Table 10: Border Counties Difference-in-Difference Regression Results – Excluding Tristate CZs

VARIABLES	(1) Eviction Rate	(2) Eviction Rate	(3) Eviction Rate	(4) Eviction Rate
Medicaid*Post	-0.248**	-0.205*	-0.224**	-0.198*
	(0.0981)	(0.101)	(0.106)	(0.108)
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Commuting Zone FE * Year FE	Yes	Yes	Yes	Yes
Demographic Controls	No	Yes	No	Yes
Economic Controls	No	No	Yes	Yes
Mean Eviction Rate	1.70	1.70	1.70	1.70
Coefficient as % of Mean	14.6%	12.1%	13.2%	11.6%
Number of States (inc. D.C.)	26	26	26	26
Number of Counties	185	185	185	185
Number of Commuting Zones	38	38	38	38
Observations	1,892	1,892	1,892	1,892

Notes: Eviction rate is measured as the number of evictions per 100 renting households. Regressions exclude singleton observations and commuting zones stretching across three states. Louisiana is not included as an expansion state in 2016. Eviction data from states with varying levels of data collection across time are excluded. These dropped data are from Washington D.C. in 2005, Maine in 2005-2006, New Hampshire in 2015-2016, New York in 2007-2016, Rhode Island in 2005-2007 and 2013-2014, South Carolina in 2005-2008 and 2016, New Jersey in 2005 and 2016, West Virginia in 2005-2006, Massachusetts in 2005-2007, and all Pennsylvania data. Robust standard errors are clustered at states and are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Sources: The Eviction Lab, Census Small Area Health Insurance Estimates, Census American Community Survey 5-Year Estimates, 2010 Census

Table 11: Border Counties Difference-in-Differences 2013 Means – Excluding Tri-state CZs

2013 Mean	Non-Expansion	Expansion
Eviction Rate	1.97	1.55
Uninsured Rate	15.14	14.76
Unemployment Rate	7.40	7.22
Median Household Income	\$47,344	\$51.096
Median Gross Rent	\$694	\$735
Median Rent as Percent of Income	29.15	29.46
Household Size	2.50	2.54
% Female	49.98%	50.29%
% African-American	7.51%	6.61%
% Less Than HS	14.60%	14.25%
% High School	35.99%	33.01%
% Some College	29.90%	30.18%
% College	12.83%	14.89%
% More Than College	6.69%	4.14%
Counties	80	69

Notes: Eviction rate is measured as the number of evictions per 100 renting households. Regressions exclude singleton observations. Louisiana is not included as an expansion state in 2016. Eviction data from states with varying levels of data collection across time are excluded. These dropped data are from Washington D.C. in 2005, Maine in 2005-2006, New Hampshire in 2015-2016, New York in 2007-2016, Rhode Island in 2005-2007 and 2013-2014, South Carolina in 2005-2008 and 2016, New Jersey in 2005 and 2016, West Virginia in 2005-2006, Massachusetts in 2005-2007, and all Pennsylvania data. Robust standard errors are clustered at states and are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Sources: The Eviction Lab, Census Small Area Health Insurance Estimates, Census American Community Survey 5-Year Estimates, 2010 Census

Table 12: Difference-in-Difference-in-Differences Regression Results

VARIABLES	(1) Eviction Rate	(2) Eviction Rate	(3) Eviction Rate	(4) Eviction Rate	(5) Eviction Rate	(6) Eviction Rate
Uninsured*Medicaid*Post	0.0200	0.0236	0.0203	-0.00998	-0.0132	-0.0109
	(0.0353)	(0.0356)	(0.0349)	(0.0228)	(0.0227)	(0.0225)
Uninsured*Post	0.0278*	0.0332**	0.0269**	0.0289*	0.0267*	0.0269*
	(0.0138)	(0.0140)	(0.0134)	(0.0147)	(0.0135)	(0.0137)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	No	Yes	Yes	No	Yes
Economic Controls	No	Yes	Yes	No	Yes	Yes
State FE X Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County Linear Time Trends	No	No	No	Yes	Yes	Yes
Mean Eviction Rate	2.03	2.03	2.03	2.03	2.03	2.03
Number of States (inc. D.C.)	47	47	47	47	47	47
Number of Counties	2,734	2,734	2,734	2,734	2,734	2,734
Observations	27,940	27,934	27,934	27,940	27,934	27,934

Notes: Eviction rate is measured as the number of evictions per 100 renting households. Regressions exclude singleton observations. Eviction data from states with varying levels of data collection across time are excluded. These dropped data are from Washington D.C. in 2005, Maine in 2005-2006, New Hampshire in 2015-2016, New York in 2007-2016, Rhode Island in 2005-2007 and 2013-2014, South Carolina in 2005-2008 and 2016, New Jersey in 2005 and 2016, West Virginia in 2005-2006, Massachusetts in 2005-2007, and all Pennsylvania data. Robust standard errors are clustered at states and are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Sources: The Eviction Lab, Census Small Area Health Insurance Estimates, Census American Community Survey 5-Year Estimates, 2010 Census

Table 13: Difference-in-Difference-in-Differences Regression Results - Robustness Checks

VARIABLES	(1) *Weighted* Eviction Rate	(2) *Balanced* Eviction Rate	(3) *Dropped States* Eviction Rate	(4) *<400% FPL* Eviction Rate	(5) *Top Quartile Rent Burden* Eviction Rate
Uninsured*Medicaid*Post	-0.0156	-0.0115	-0.0271	-0.00878	-0.00445
	(0.0344)	(0.0367)	(0.0176)	(0.0123)	(0.0501)
Uninsured*Post	0.0111	0.0337*	0.0234	0.00209	0.0279
	(0.0227)	(0.0190)	(0.0139)	(0.00425)	(0.0282)
Year FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Demographic Controls	Yes	Yes	Yes	Yes	Yes
Economic Controls	Yes	Yes	Yes	Yes	Yes
State FE X Year FE	Yes	Yes	Yes	Yes	Yes
County Linear Time Trends	Yes	Yes	Yes	Yes	Yes
Mean Eviction Rate	2.03	2.47	1.92	1.99	2.60
Number of States (inc. D.C.)	36	47	41	46	41
Number of Counties	2,734	1,538	2,493	2,664	700
Observations	27,934	18,452	27,934	27,934	6,994

Notes: Eviction rate is measured as the number of evictions per 100 renting households. Regressions exclude singleton observations. Eviction data from states with varying levels of data collection across time are excluded. These dropped data are from Washington D.C. in 2005, Maine in 2005-2006, New Hampshire in 2015-2016, New York in 2007-2016, Rhode Island in 2005-2007 and 2013-2014, South Carolina in 2005-2008 and 2016, New Jersey in 2005 and 2016, West Virginia in 2005-2006, Massachusetts in 2005-2007, and all Pennsylvania data. Robust standard errors are clustered at states and are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Sources: The Eviction Lab, Census Small Area Health Insurance Estimates, Census American Community Survey 5-Year Estimates, 2010 Census

Table 14: Instrumental Variable Model - First Stage Regression Results

	(1)	(2)
VARIABLES	Post-Uninsured Rate	Post-Uninsured Rate
Pre-Uninsured*Medicaid*Post	-0.225***	-0.357***
	(0.0492)	(0.0491)
Pre-Uninsured*Post	0.0827**	-0.0560***
	(0.0353)	(0.0175)
Year FE	Yes	Yes
County FE	Yes	Yes
Demographic Controls	Yes	Yes
Economic Controls	Yes	Yes
State FE X Year FE	Yes	Yes
County Linear Time Trends	No	Yes
Number of States (inc. D.C.)	47	47
Number of Counties	2,734	2,734
Observations	27,940	27,934

Notes: Uninsured rates in interaction terms are pre-treatment averages. Eviction rate is measured as the number of evictions per 100 renting households. Regressions exclude singleton observations. Data from states with varying levels of eviction data collection across time are excluded. These dropped data are from Washington D.C. in 2005, Maine in 2005-2006, New Hampshire in 2015-2016, New York in 2007-2016, Rhode Island in 2005-2007 and 2013-2014, South Carolina in 2005-2008 and 2016, New Jersey in 2005 and 2016, West Virginia in 2005-2006, Massachusetts in 2005-2007, and all Pennsylvania data. Robust standard errors are clustered at states and are in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Sources: The Eviction Lab, Census Small Area Health Insurance Estimates, Census American Community Survey 5-Year Estimates, 2010 Census

Table 15: Instrumental Variable Model - Second Stage Regression Results

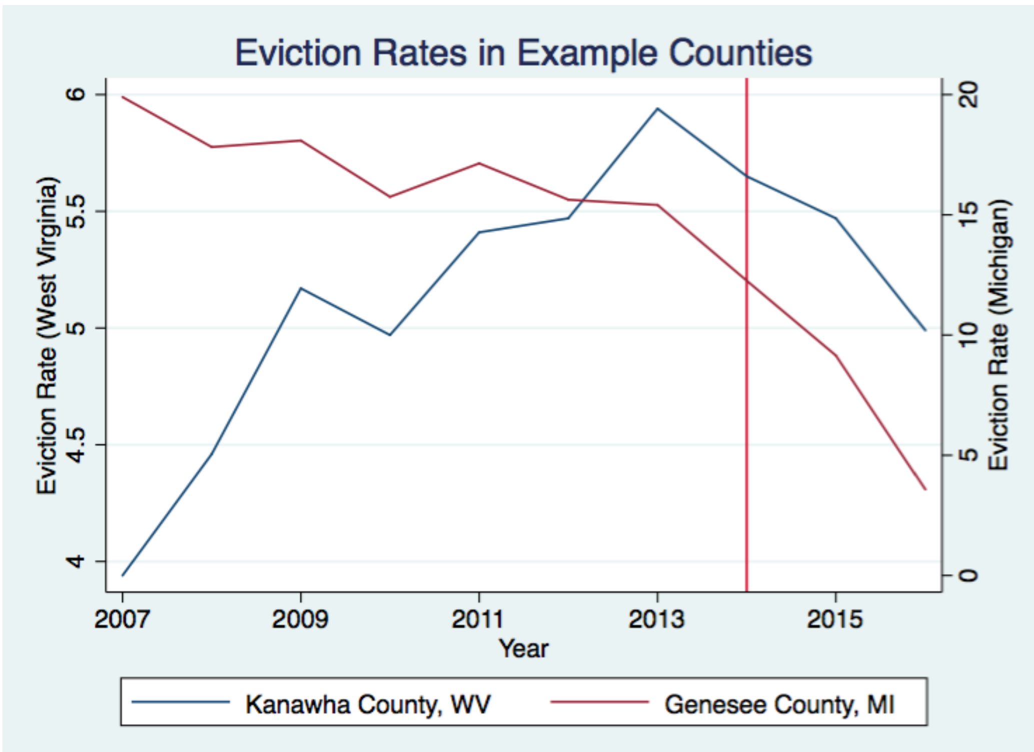
VARIABLES	(1) Eviction Rate	(2) Eviction Rate
Uninsured Rate	-0.0646	0.0343
	(0.0449)	(0.0651)
Instrument(s)	DDD, Uninsured*Post	DDD
Homoskedastic F-Test	207.80	248.20
Heteroskedastic F-Test	49.58	42.32
Number of Counties	2,734	2,734
Observations	27,940	27,940
Year FE	Yes	Yes
County FE	Yes	Yes
Demographic Controls	Yes	Yes
Economic Controls	Yes	Yes
State FE X Year FE	Yes	Yes
County Linear Time Trends	Yes	Yes

Notes: Uninsured rates in interaction terms are pre-treatment averages. Eviction rate is measured as the number of evictions per 100 renting households. Regressions exclude singleton observations. Eviction data from states with varying levels of data collection across time are excluded. These dropped data are from Washington D.C. in 2005, Maine in 2005-2006, New Hampshire in 2015-2016, New York in 2007-2016, Rhode Island in 2005-2007 and 2013-2014, South Carolina in 2005-2008 and 2016, New Jersey in 2005 and 2016, West Virginia in 2005-2006, Massachusetts in 2005-2007, and all Pennsylvania data. Robust standard errors are clustered at states and are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Sources: The Eviction Lab, Census Small Area Health Insurance Estimates, Census American Community Survey 5-Year Estimates, 2010 Census

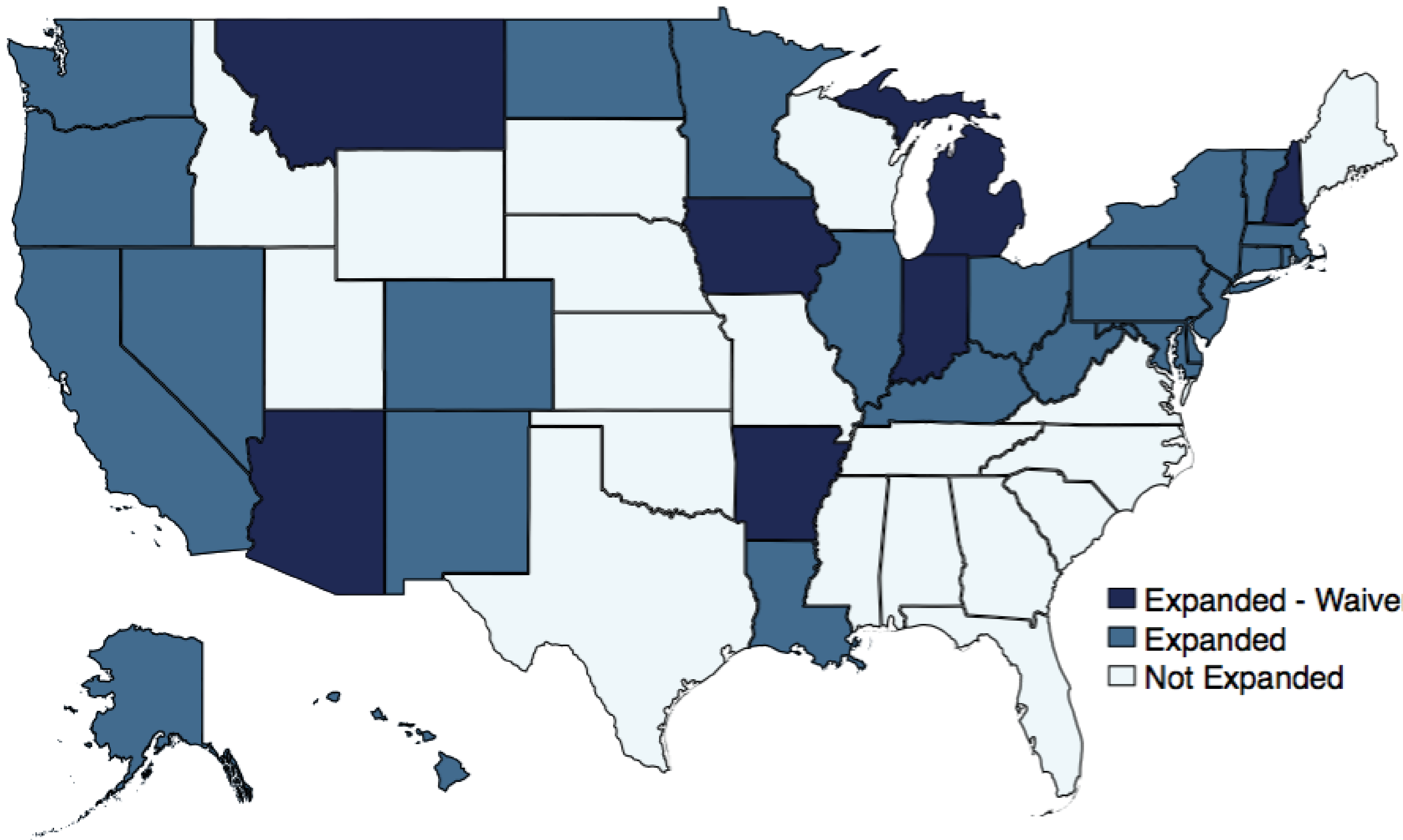
8 Figures

Figure 1: Eviction Rates in Kanawha and Genesee Counties



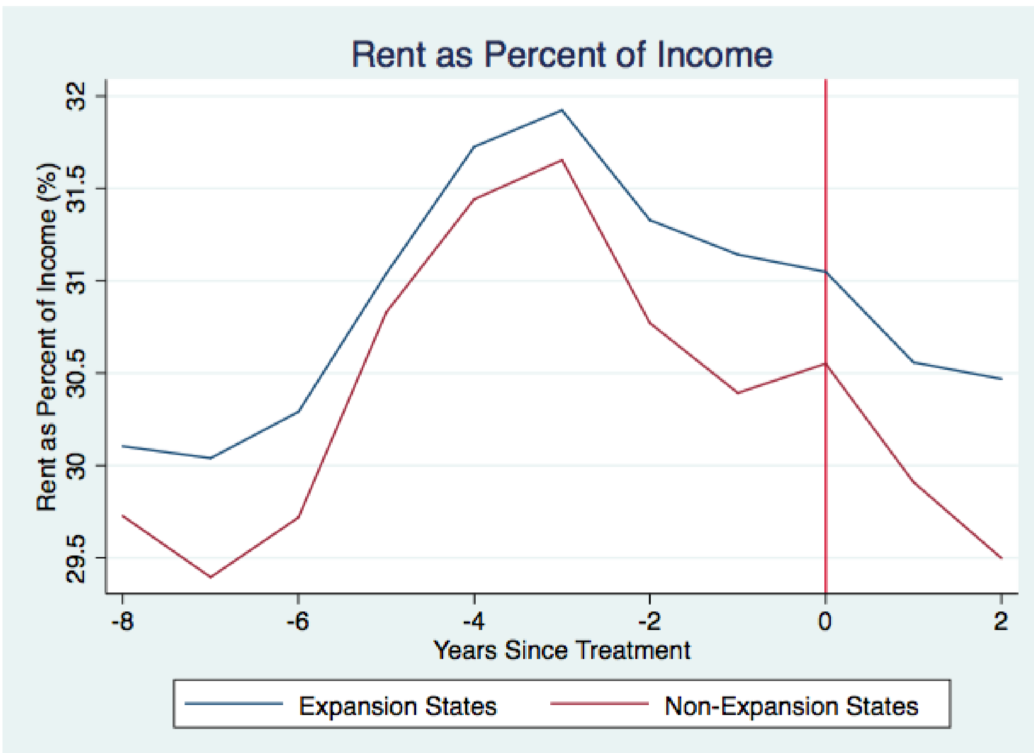
Notes: The reference line marks 2014, the year in which both West Virginia and Michigan expanded Medicaid. Eviction rates are measured as evictions per 100 renting households.
Source: The Eviction Lab, American Community Survey 5-Year Estimates, The 2010 Census

Figure 2: 2017 Medicaid Expansion Status



Notes: States that expanded with a waiver used the Section 1115 waiver provision of the Affordable Care Act.
Source: Kaiser Family Foundation

Figure 3: Rent as Percent of Income: Expansion States vs. Non-Expansion States

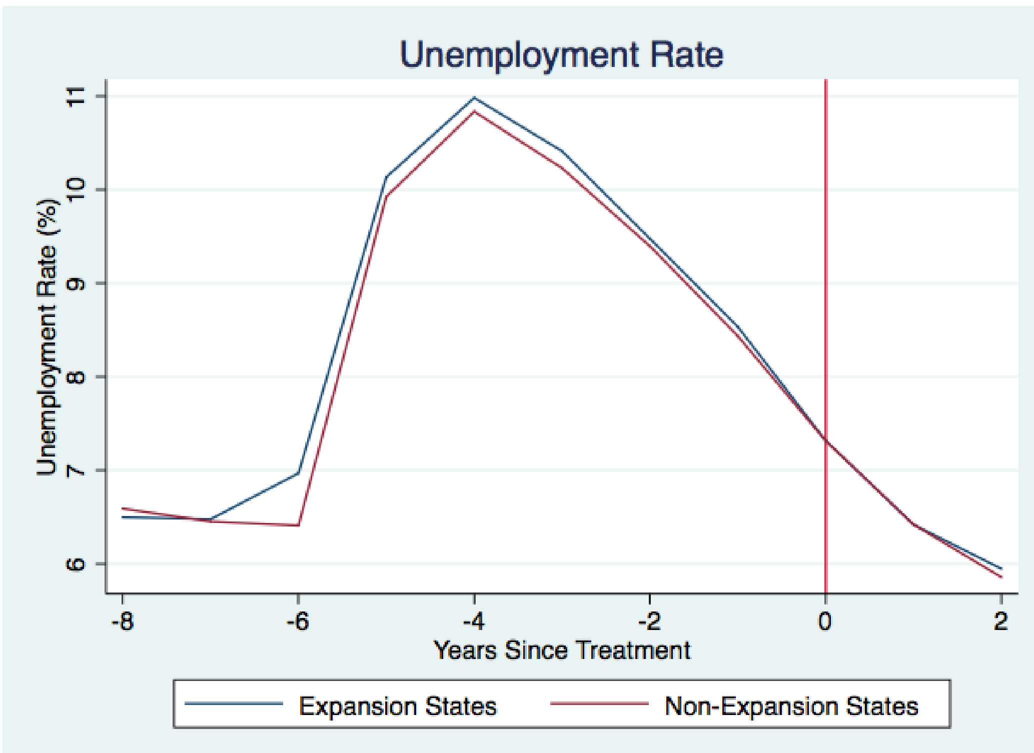


Notes: Expansion states include states that expanded Medicaid before the end of 2017. Non-expansion states include states that did not expand Medicaid by the end of 2017. If a state expanded Medicaid in the middle of a year before July, its treatment year is defined as that year. If a state expanded Medicaid in the middle of a year in July or later, its treatment year is defined as the following year. State-level data are collapsed and weighted by total population. The reference line marks the year in which a state expanded or 2014 for non-expansion states.
Source: American Community Survey 1-Year Estimates

Figure 4: Median Gross Rent: Expansion States vs. Non-Expansion States

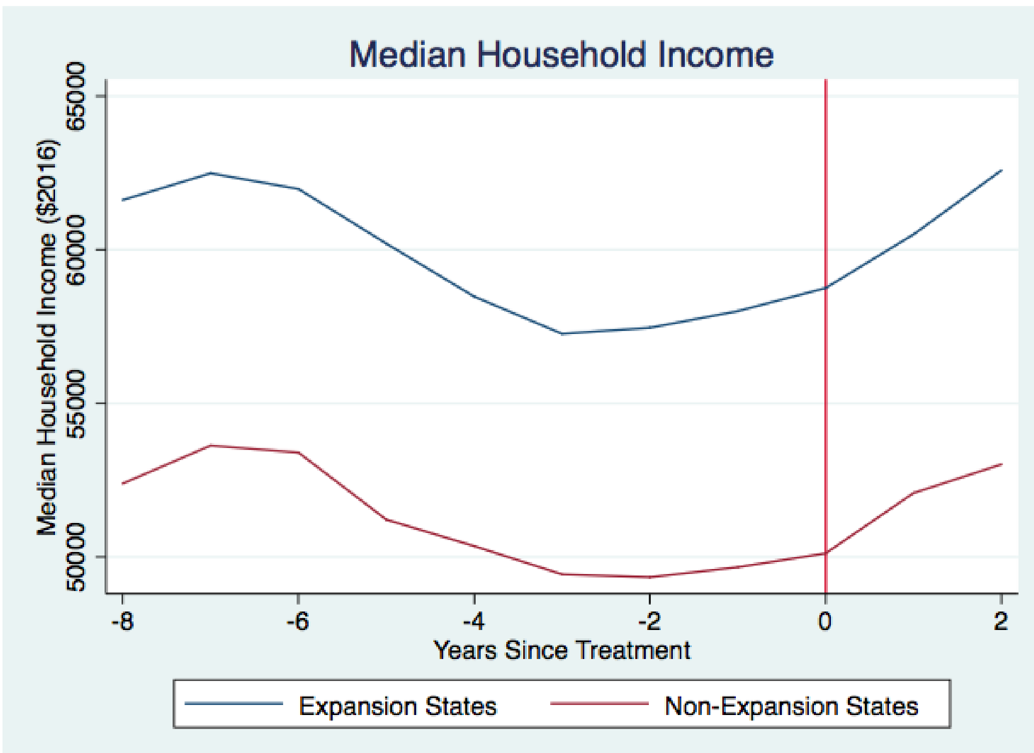
Notes: Expansion states include states that expanded Medicaid on January 1st, 2014. Non-expansion states include states that did not expand Medicaid by the end of 2017. State-level data are collapsed and weighted by total population. The reference line marks the Medicaid Expansion.
Source: American Community Survey 1-Year Estimates

Figure 5: Unemployment Rates: Expansion States vs. Non-Expansion States



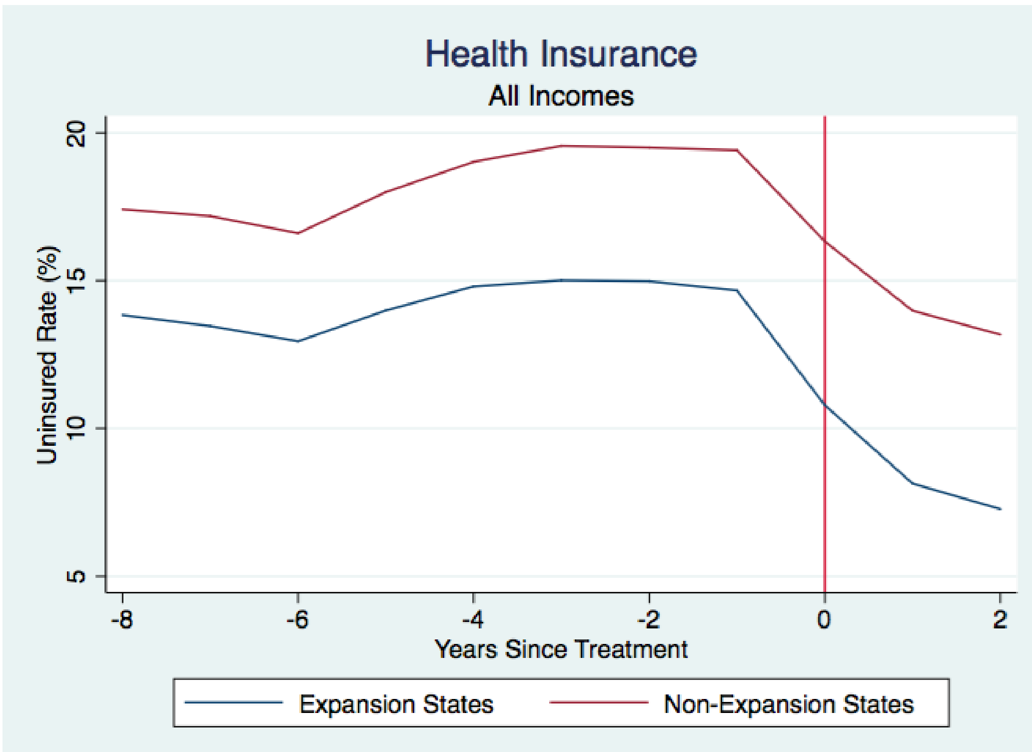
Notes: EExpansion states include states that expanded Medicaid before the end of 2017. Non-expansion states include states that did not expand Medicaid by the end of 2017. If a state expanded Medicaid in the middle of a year before July, its treatment year is defined as that year. If a state expanded Medicaid in the middle of a year in July or later, its treatment year is defined as the following year. State-level data are collapsed and weighted by total population. The reference line marks the year in which a state expanded or 2014 for non-expansion states. Source: American Community Survey 1-Year Estimates

Figure 6: Median Household Income: Expansion States vs. Non-Expansion States



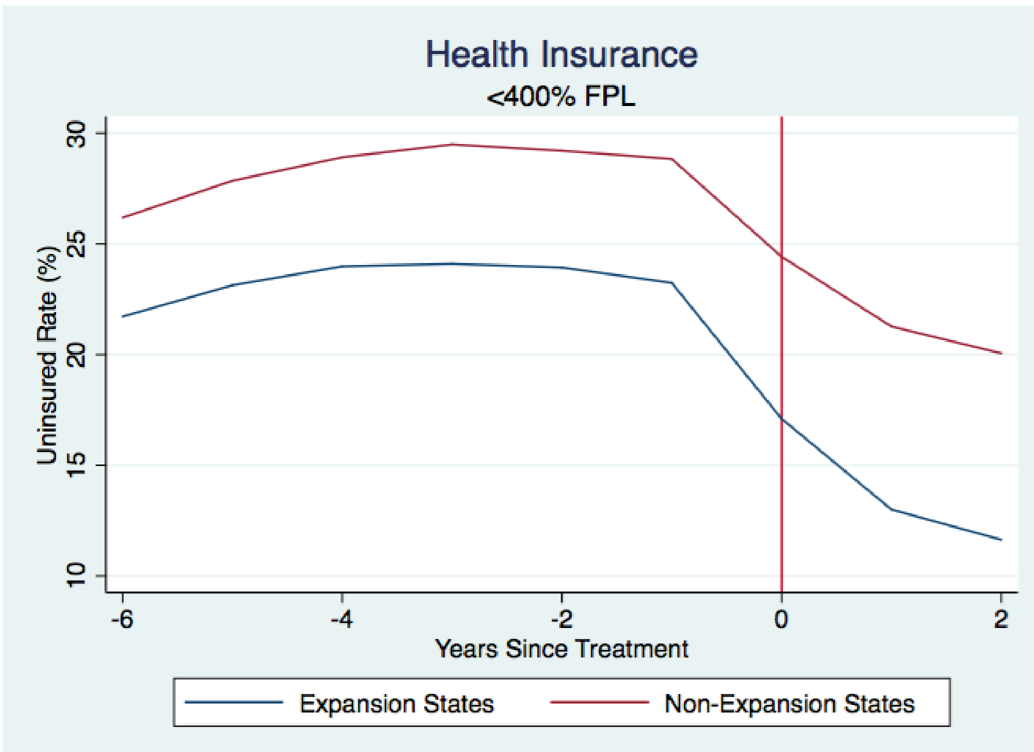
Notes: Expansion states include states that expanded Medicaid before the end of 2017. Non-expansion states include states that did not expand Medicaid by the end of 2017. If a state expanded Medicaid in the middle of a year before July, its treatment year is defined as that year. If a state expanded Medicaid in the middle of a year in July or later, its treatment year is defined as the following year. State-level data are collapsed and weighted by total population. The reference line marks the year in which a state expanded or 2014 for non-expansion states.
Source: American Community Survey 1-Year Estimates

Figure 7: Uninsured Rate: Expansion States vs. Non-Expansion States



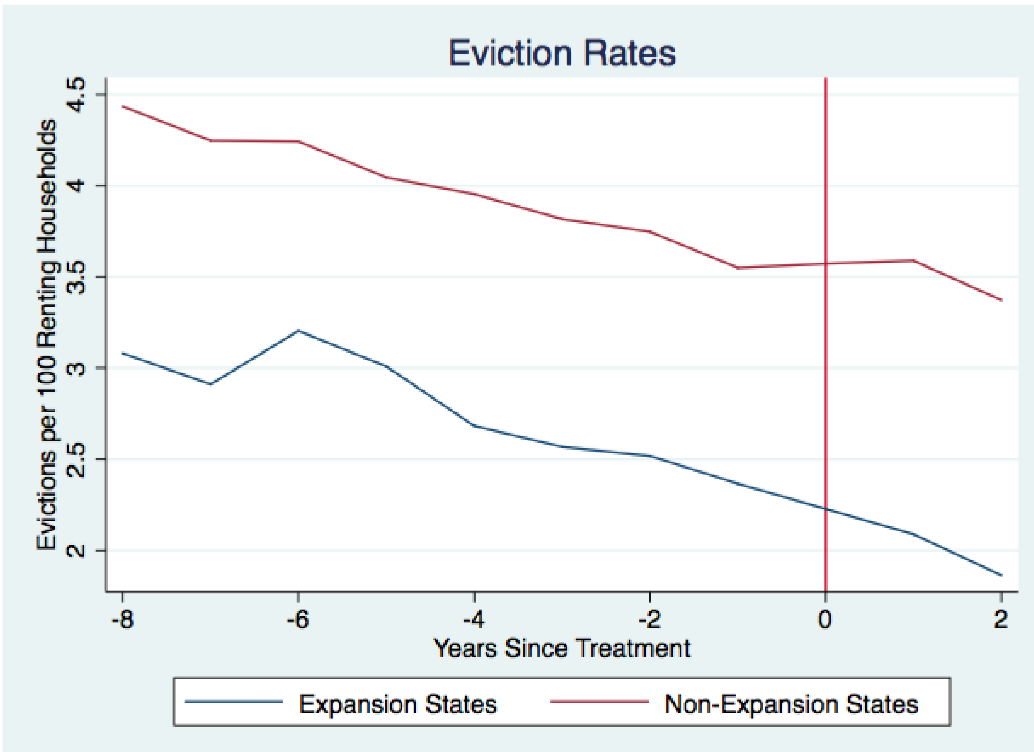
Notes: Expansion states include states that expanded Medicaid before the end of 2017. Non-expansion states include states that did not expand Medicaid by the end of 2017. If a state expanded Medicaid in the middle of a year before July, its treatment year is defined as that year. If a state expanded Medicaid in the middle of a year in July or later, its treatment year is defined as the following year. County-level data are collapsed and weighted by total population. SAHIE relied on different datasets for its estimates beginning in 2008 making comparisons between pre-2008 and post-2008 rates unreliable. The reference line marks the year in which a state expanded or 2014 for non-expansion states.
Source: Census Small Area Health Insurance Estimates

Figure 8: Uninsured Rate <400% FPL: Expansion States vs. Non-Expansion States



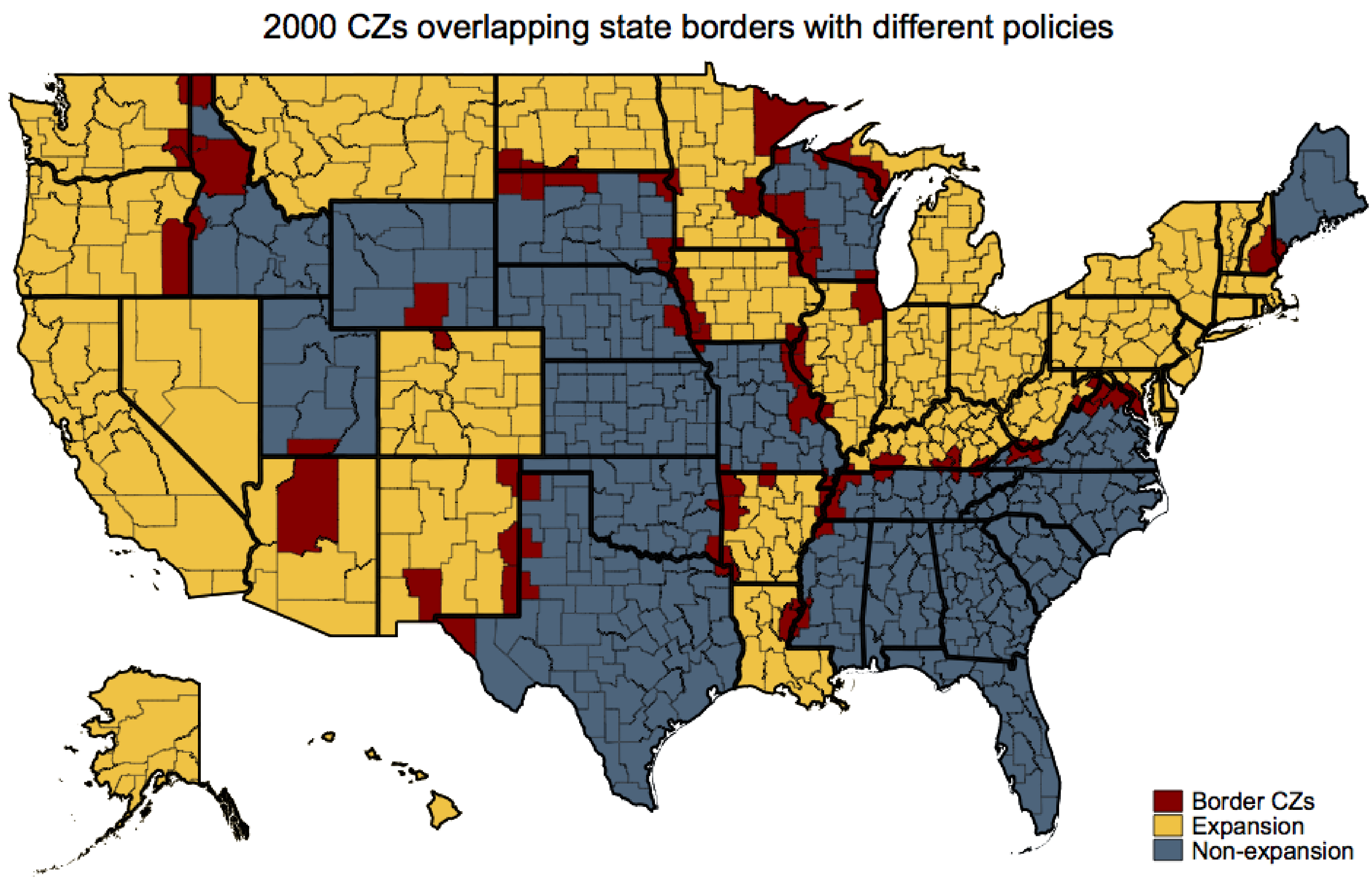
Notes: Expansion states include states that expanded Medicaid before the end of 2017. Non-expansion states include states that did not expand Medicaid by the end of 2017. If a state expanded Medicaid in the middle of a year before July, its treatment year is defined as that year. If a state expanded Medicaid in the middle of a year in July or later, its treatment year is defined as the following year. County-level data are collapsed and weighted by total population. SAHIE relied on different datasets for its estimates beginning in 2008 making comparisons between pre-2008 and post-2008 rates unreliable. The reference line marks the year in which a state expanded or 2014 for non-expansion states.
Source: Census Small Area Health Insurance Estimates

Figure 9: Eviction Rates: Expansion States vs. Non-Expansion States



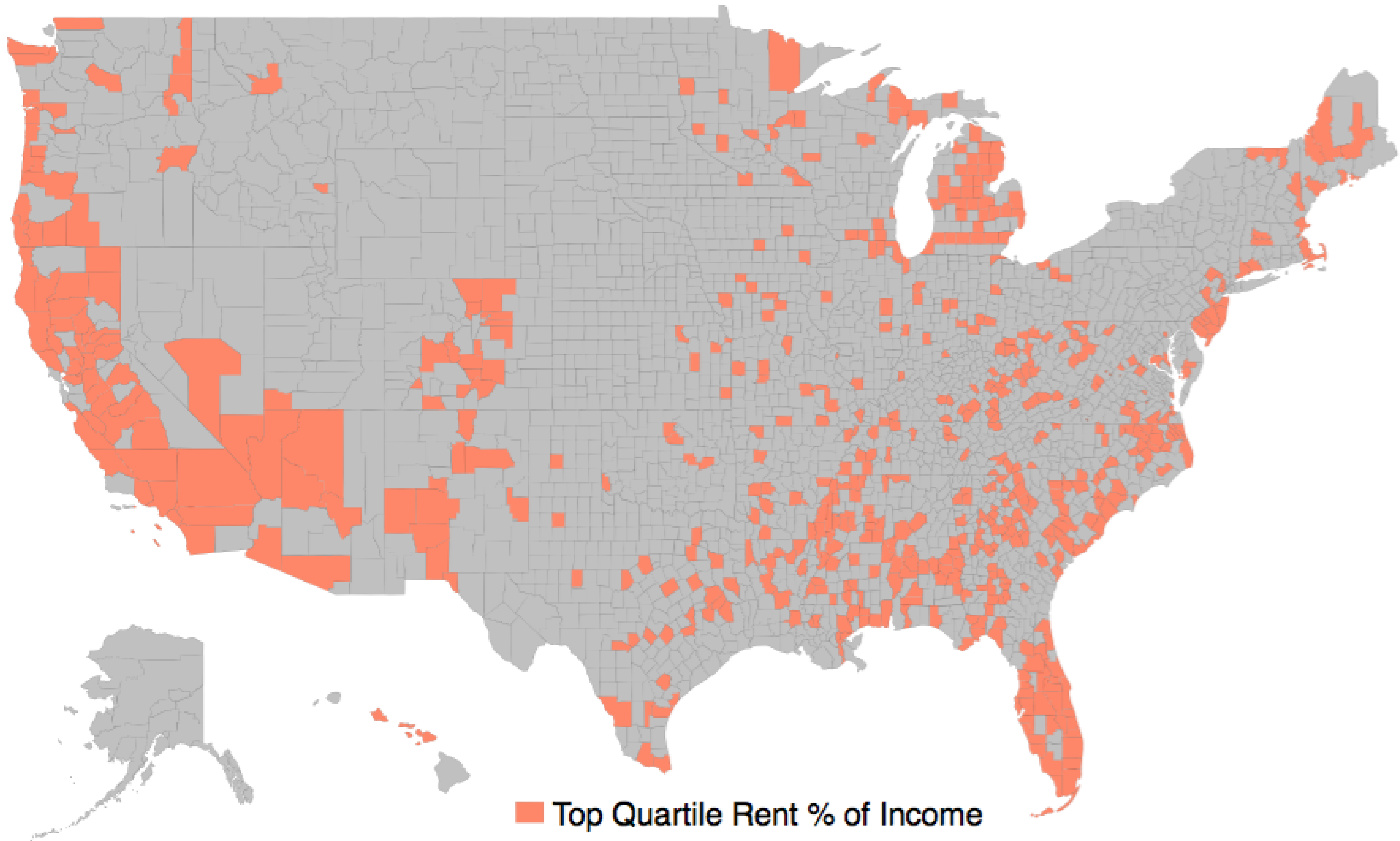
Notes: Expansion states include states that expanded Medicaid before the end of 2017. Non-expansion states include states that did not expand Medicaid by the end of 2017. If a state expanded Medicaid in the middle of a year before July, its treatment year is defined as that year. If a state expanded Medicaid in the middle of a year in July or later, its treatment year is defined as the following year. County-level data are collapsed and weighted by total population. Eviction data from states with varying levels of data collection across time are excluded. These dropped data are from Washington D.C. in 2005, Maine in 2005-2006, New Hampshire in 2015-2016, New York in 2007-2016, Rhode Island in 2005-2007 and 2013-2014, South Carolina in 2005-2008 and 2016, New Jersey in 2005 and 2016, West Virginia in 2005-2006, Massachusetts in 2005-2007, and all Pennsylvania data. The reference line marks the year in which a state expanded or 2014 for non-expansion states.
Source: The Eviction Lab, American Community Survey 5-Year Estimates, 2010 Census

Figure 10: Commuting Zones With Expansion Status Variation



Source: Kaiser Family Foundation

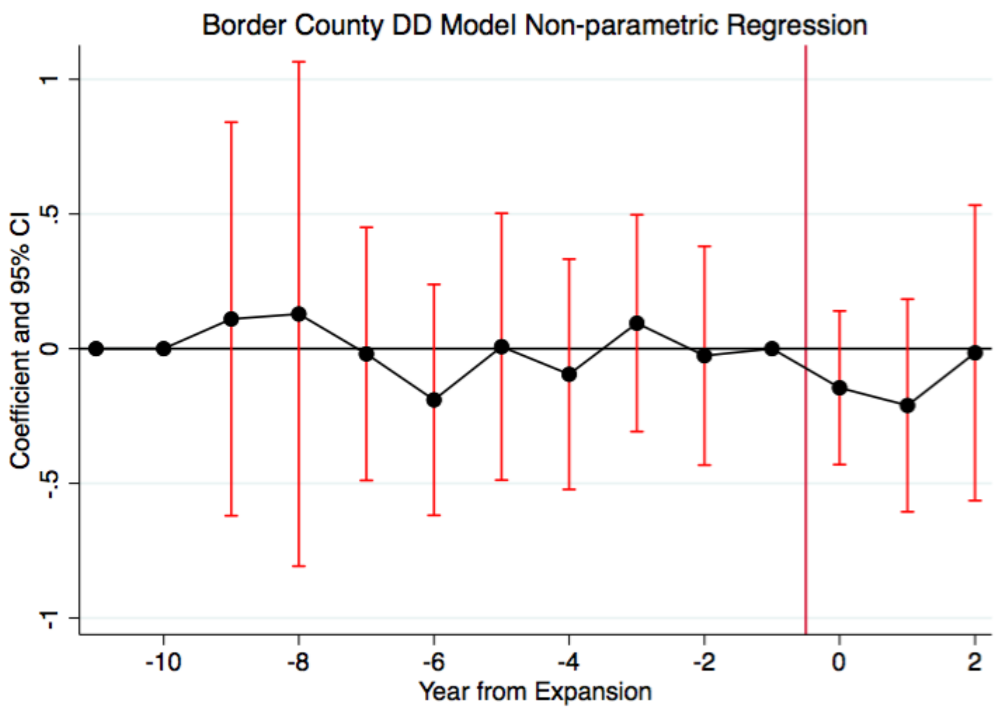
Figure 11: Top Quartile Rent-Burdened Counties



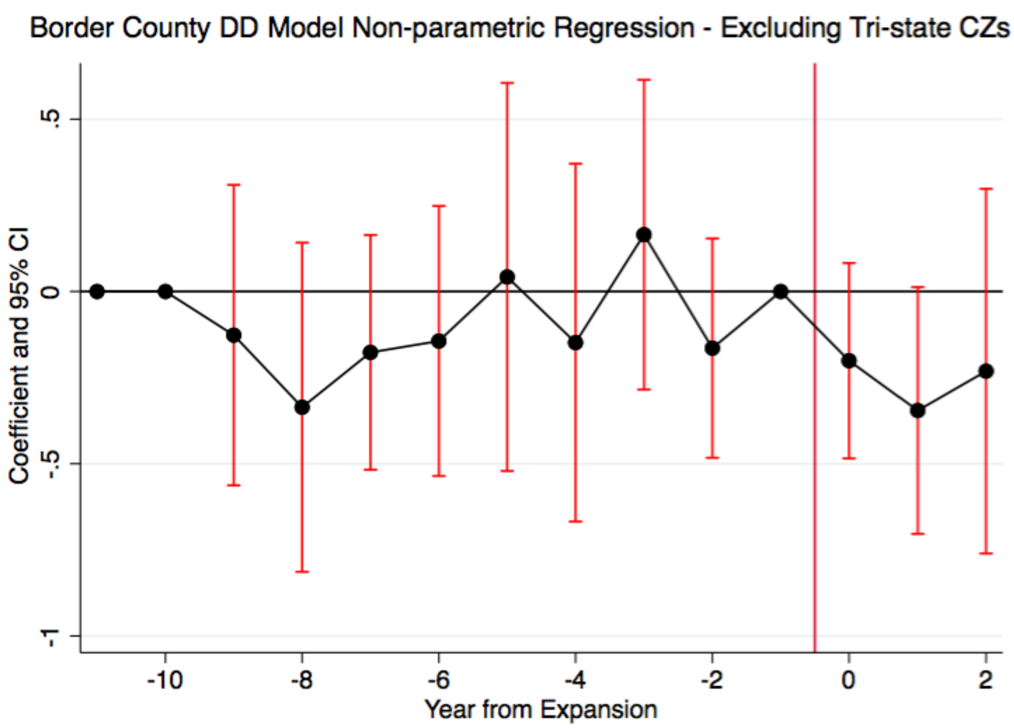
Notes: Orange counties are those in the top quartile for average rent as a percent of income before 2014. The calculation to group these counties only included counties used in regression analysis.
Source: Census American Community Survey 5-Year Estimates

Figure 12: Border County DD Non-Parametric Regressions

(a) Including all CZs



(b) Excluding Tristate CZs



Source: The Eviction Lab, American Community Survey 5-Year Estimates, 2010 Census

A Summary Statistics: Eviction and Health Insurance

Table 16: LexisNexis National Evictions Summary Statistics

Year	Evictions	Renting Households	Eviction Rate
2005	1,140,009	34,541,306	3.30
2006	1,231,859	34,549,528	3.57
2007	1,127,641	33,699,687	3.35
2008	1,123,183	33,417,264	3.36
2009	1,096,682	33,592,469	3.26
2010	1,131,009	36,683,953	3.08
2011	1,129,127	38,598,095	2.92
2012	1,109,150	38,937,072	2.85
2013	1,037,120	38,867,929	2.67
2014	1,036,717	39,429,063	2.63
2015	1,003,041	39,500,902	2.54
2016	982,157	39,120,334	2.51

Notes: Eviction counts include all raw data provided to The Eviction Lab by LexisNexis. The number of renting households are a summation of renting households from counties with eviction data. Eviction rate is measured as evictions per 100 renting households. Sources: The Eviction Lab, Census American Community Survey 5-Year Estimates, 2010 Census

Table 17: LexisNexis Eviction Rates Across States

State	2013 Eviction Rate	2014 Eviction Rate	2015 Eviction Rate	2016 Eviction Rate
Alabama	2.02	1.79	1.95	1.96
Alaska	0.49	0.62	1.18	1.61
Arizona	5.79	5.42	4.92	4.86
Arkansas	0.077	0.038	0.041	0.022
California	1.10	1.13	1.00	0.93
Colorado	1.52	0.99	1.73	2.93
Connecticut	3.03	3.04	3.10	3.15
Delaware	6.79	6.34	6.33	6.05
District of Columbia	2.53	4.10	4.17	3.54
Florida	2.77	2.80	2.85	2.84
Georgia	5.68	5.56	6.04	5.22
Hawaii	0.51	0.43	0.26	0.13
Idaho	0.83	0.77	0.84	0.77
Illinois	2.18	2.09	1.87	1.72
Indiana	4.63	4.54	4.00	4.33
Iowa	1.99	2.06	2.20	2.21
Kansas	2.73	2.79	2.20	2.43
Kentucky	3.76	3.33	3.35	3.01
Louisiana	2.68	3.25	3.21	2.79
Maine	2.54	2.52	2.60	2.47
Maryland	0.43	0.77	0.90	1.36
Massachusetts	2.04	2.01	1.95	1.64
Michigan	6.96	6.13	4.32	3.36
Minnesota	1.36	1.17	0.75	0.59
Mississippi	4.71	4.90	5.09	4.89
Missouri	3.54	2.93	3.20	3.10
Montana	0.87	0.99	0.96	1.00
Nebraska	2.39	2.47	2.42	2.45
Nevada	4.56	4.25	4.47	3.61
New Hampshire	0.90	1.93	**0.38**	**0.16**
New Jersey	1.46	1.47	0.21	**0.0034**
New Mexico	3.64	3.07	2.88	2.74
New York	**0.55**	**0.86**	**1.05**	**1.67**
North Carolina	5.40	5.59	5.56	5.66
Ohio	4.13	3.69	3.92	3.29
Oklahoma	3.84	4.15	4.70	4.83
Oregon	1.21	1.03	1.20	1.22
Pennsylvania	**0.74**	**2.04**	**0.97**	**0.0056**
Rhode Island	**0.65**	**0.53**	3.59	3.38
South Carolina	4.45	4.04	4.27	**9.02**
Tennessee	2.41	2.60	2.94	2.53
Texas	2.80	2.88	2.70	2.33
Utah	1.07	1.32	1.05	1.02
Vermont	0.11	0.14	0.15	0.089
Virginia	6.55	6.75	6.41	6.22
Washington	0.77	0.71	0.80	0.84
West Virginia	4.35	4.40	4.09	4.18
Wisconsin	2.22	2.25	2.16	2.03
Wyoming	0.18	0.25	0.47	0.89

Notes: Eviction counts include all raw data provided to The Eviction Lab by LexisNexis. The number of renting households are a summation of renting households from counties with eviction data. Eviction rate is measured as evictions per 100 renting households. Bolded data are dropped from regression analysis.
Sources: The Eviction Lab, Census American Community Survey 5-Year Estimates

Table 18: 2016 LexisNexis State Eviction Summary Statistics

State	Evictions	Renting Households	Eviction Rate
Alabama	11,348	579,180	1.96
Alaska	675	42,055	1.61
Arizona	42,403	872,557	4.86
Arkansas	26	118,253	0.22
California	51,272	5,537,783	0.93
Colorado	21,161	721,777	2.93
Connecticut	14,079	446,356	3.15
Delaware	6,001	99,173	6.05
District of Columbia	5,680	160,640	3.54
Florida	71,689	2,523,712	2.84
Georgia	60,462	1,159,173	5.22
Hawaii	258	194,131	0.13
Idaho	1,263	164,586	0.77
Illinois	27,457	1,596,087	1.72
Indiana	33,480	772,462	4.33
Iowa	7,775	351,669	2.21
Kansas	8,795	362,255	2.43
Kentucky	13,390	444,948	3.01
Louisiana	14,325	513,638	2.79
Maine	3,938	159,289	2.47
Maryland	8,430	620,034	1.36
Massachusetts	15,798	966,054	1.64
Michigan	36,709	1,092,919	3.36
Minnesota	3,544	601,760	0.59
Mississippi	13,674	279,857	4.89
Missouri	21,114	680,296	3.10
Montana	1,297	130,286	1.00
Nebraska	5,941	242,811	2.45
Nevada	16,461	456,088	3.61
New Hampshire	**247**	**151,076**	**0.16**
New Jersey	**39**	**1,133,379**	**0.0034**
New Mexico	6,584	240,128	2.74
New York	**52,091**	**3,116,246**	**1.67**
North Carolina	74,532	1,316,509	5.66
Ohio	50,782	1,544,640	3.29
Oklahoma	23,739	491,848	4.83
Oregon	7,224	591,342	1.22
Pennsylvania	**30**	**531,338**	**0.0056**
Rhode Island	5,341	158,085	3.38
South Carolina	**48,983**	**543,101**	**9.02**
Tennessee	19,163	756,918	2.53
Texas	77,958	3,348,393	2.33
Utah	2,803	276,080	1.02
Vermont	59	66,351	0.089
Virginia	61,811	993,330	6.22
Washington	8,150	971,687	0.84
West Virginia	8,514	203,625	4.18
Wisconsin	15,284	751,526	2.03
Wyoming	398	44,904	0.89

Notes: Eviction counts include all raw data provided to The Eviction Lab by LexisNexis. The number of renting households are a summation of renting households from counties with eviction data. Eviction rate is measured as evictions per 100 renting households. Bolded data are dropped from regression analysis.
Sources: The Eviction Lab, Census American Community Survey 5-Year Estimates

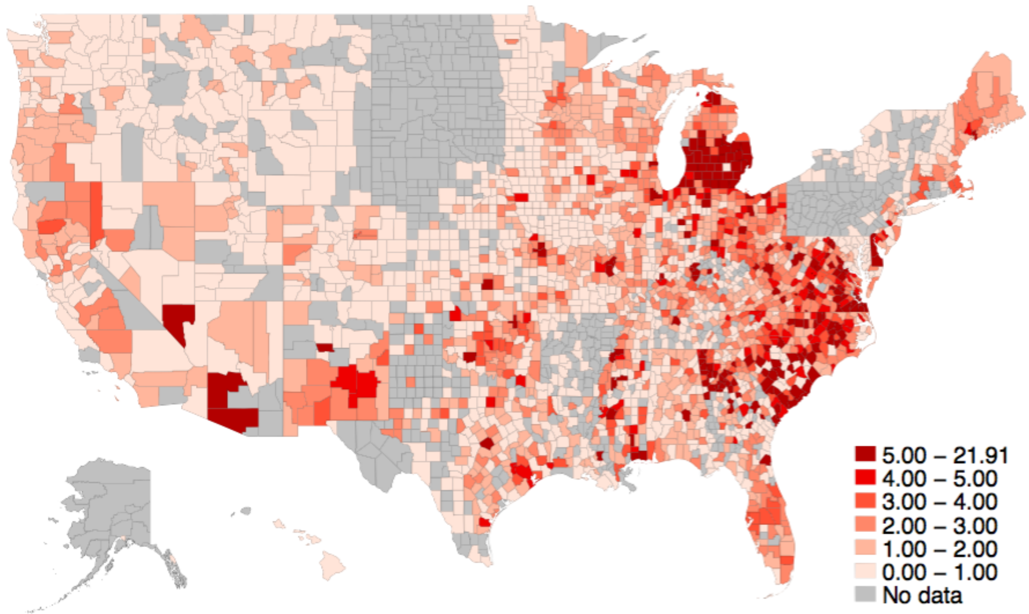
Table 19: State Health Insurance Rates

State	2013 Uninsured Rate (%)	2016 Uninsured Rate (%)	Change	Expansion State?
Alabama	13.6	9.1	-4.5	No
Alaska	18.5	14.0	-4.5	Yes
Arizona	17.1	10.0	-7.1	Yes
Arkansas	16.0	7.9	-8.1	Yes
California	17.2	7.3	-9.9	Yes
Colorado	14.1	7.5	-6.6	Yes
Connecticut	9.4	4.9	-4.5	Yes
Delaware	9.1	5.7	-3.4	Yes
District of Columbia	6.7	3.9	-2.8	Yes
Florida	20.0	12.5	-7.5	No
Georgia	18.8	12.9	-5.9	No
Hawaii	6.7	3.5	-3.2	Yes
Idaho	16.2	10.1	-6.1	No
Illinois	12.7	6.5	-6.2	Yes
Indiana	14.0	8.1	-5.9	Yes
Iowa	8.1	4.3	-3.8	Yes
Kansas	12.3	8.7	-3.6	No
Kentucky	14.3	5.1	-9.1	Yes
Louisiana	16.6	10.3	-6.3	Yes
Maine	11.2	8.0	-3.2	No
Maryland	10.2	6.1	-4.1	Yes
Massachusetts	3.7	2.5	-1.2	Yes
Michigan	11.0	5.4	-5.6	Yes
Minnesota	8.2	4.1	-4.1	Yes
Mississippi	17.1	11.8	-5.3	No
Missouri	13.0	8.9	-4.1	No
Montana	16.5	8.1	-8.4	Yes
Nebraska	11.3	8.6	-2.7	No
Nevada	20.7	11.4	-9.3	Yes
New Hampshire	10.7	5.9	-4.8	Yes
New Jersey	13.2	8.0	-5.2	Yes
New Mexico	18.6	9.2	-9.4	Yes
New York	10.7	6.1	-4.6	Yes
North Carolina	15.6	10.4	-5.2	No
North Dakota	10.4	7.0	-3.4	Yes
Ohio	11.0	5.6	-5.4	Yes
Oklahoma	17.7	13.8	-3.9	No
Oregon	14.7	6.2	-8.5	Yes
Pennsylvania	9.7	5.6	-4.1	Yes
Rhode Island	11.6	4.3	-7.3	Yes
South Carolina	15.8	10.0	-5.8	No
South Dakota	11.3	8.7	-2.6	No
Tennessee	13.9	9.0	-4.9	No
Texas	22.1	16.6	-5.5	No
Utah	14.0	8.8	-5.2	No
Vermont	7.2	3.7	-3.5	Yes
Virginia	12.3	8.7	-3.6	No
Washington	14.0	6.0	-8.0	Yes
West Virginia	14.0	5.3	-8.7	Yes
Wisconsin	9.1	5.3	-3.8	No
Wyoming	13.4	11.5	-1.9	No

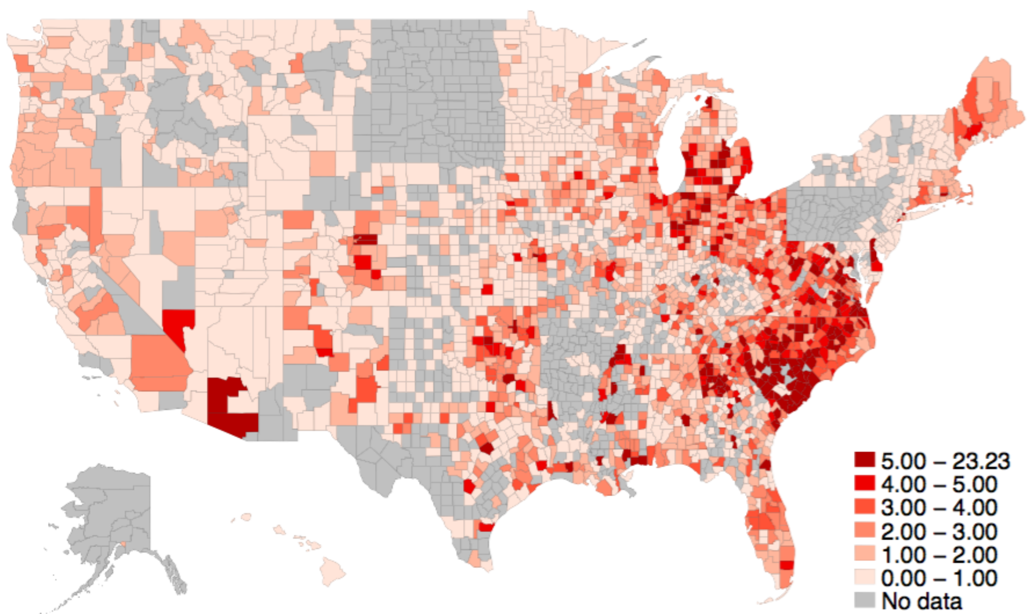
Notes: Louisiana expanded Medicaid in July of 2016.
Source: Census American Community Survey 1-Year Estimates

Figure 13: 2013 & 2016 County-Level Eviction Rates

(a) 2013



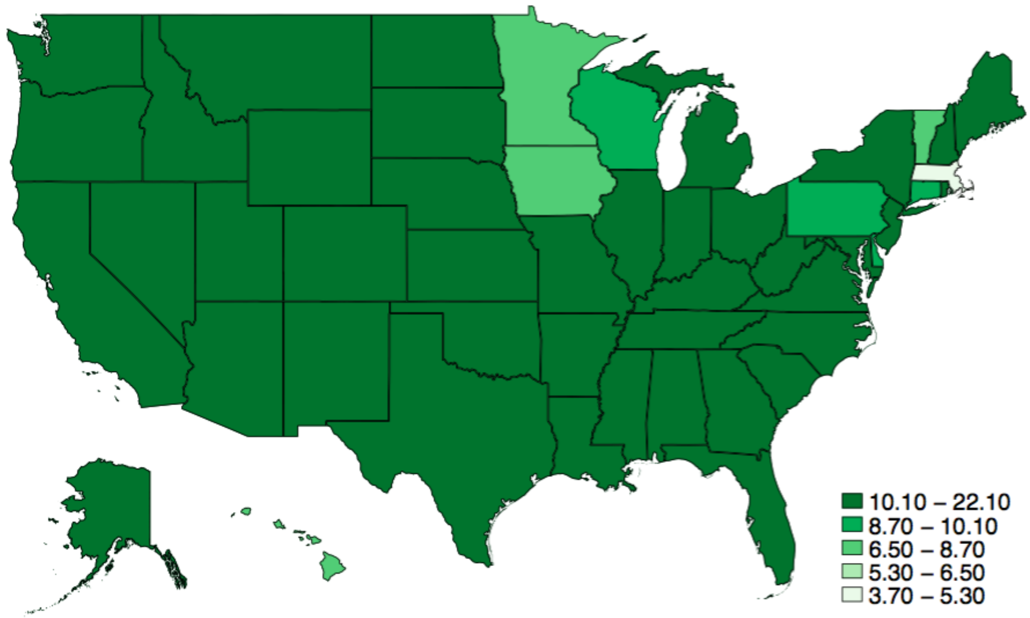
(b) 2016



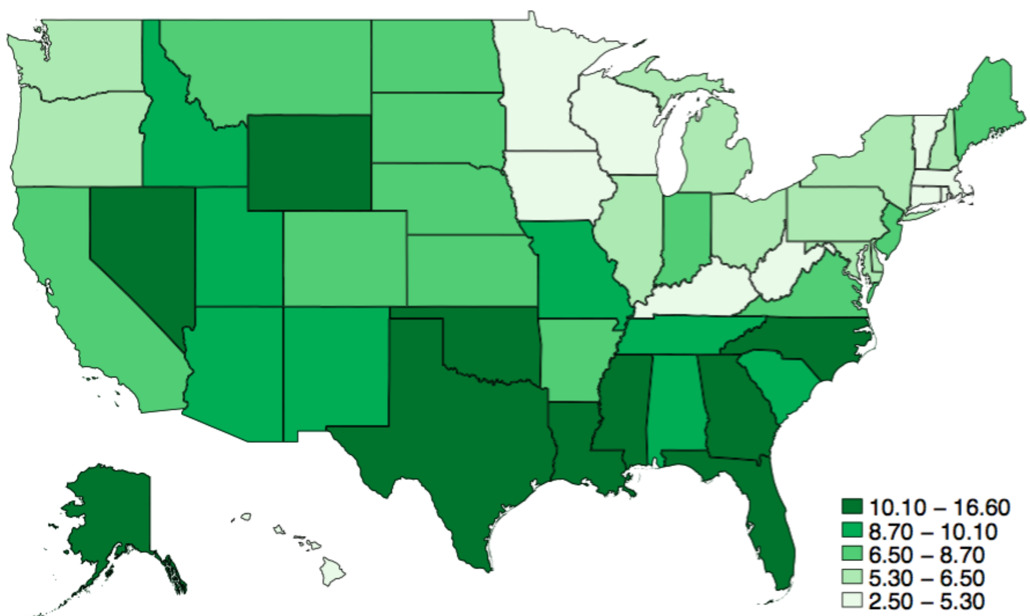
Notes: Eviction data are raw eviction counts from LexisNexis. Eviction rate is the number of evictions per 100 renting households.
Source: The Eviction Lab, American Community Survey 5-Year Estimate 2011-2016

Figure 14: 2013 & 2016 State-Level Uninsured Rates

(a) 2013



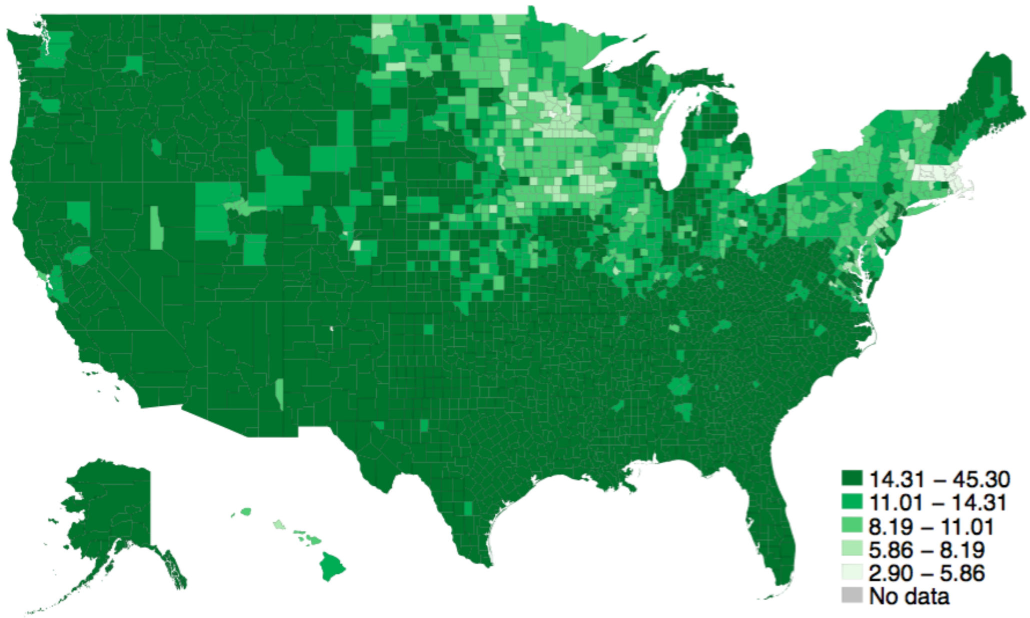
(b) 2016



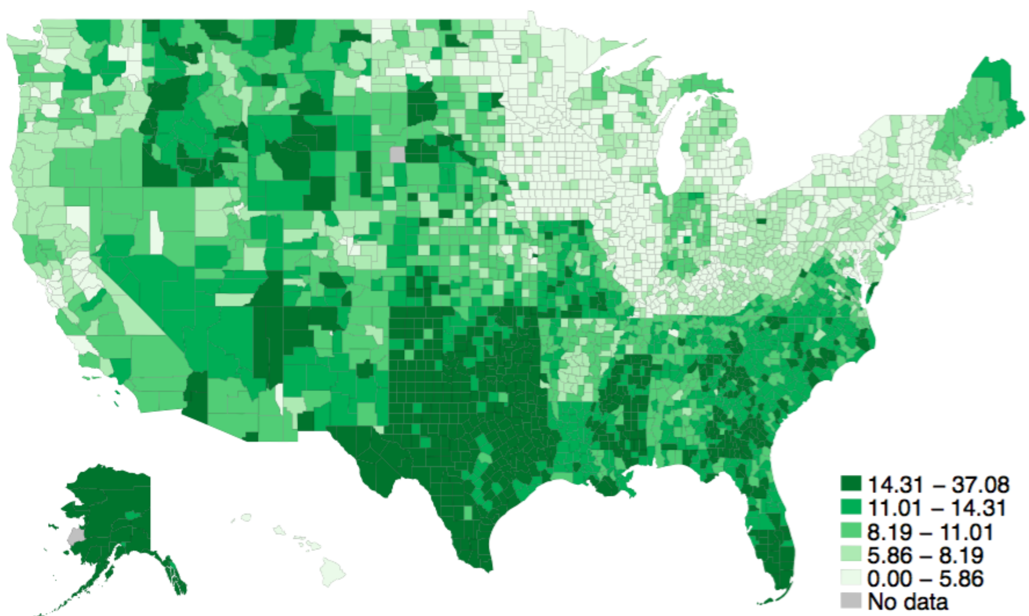
Notes: Bins indicate 2016 quintiles.
Source: Census American Community Survey 1-Year Estimates

Figure 15: 2013 & 2016 County-Level Uninsured Rates

(a) 2013



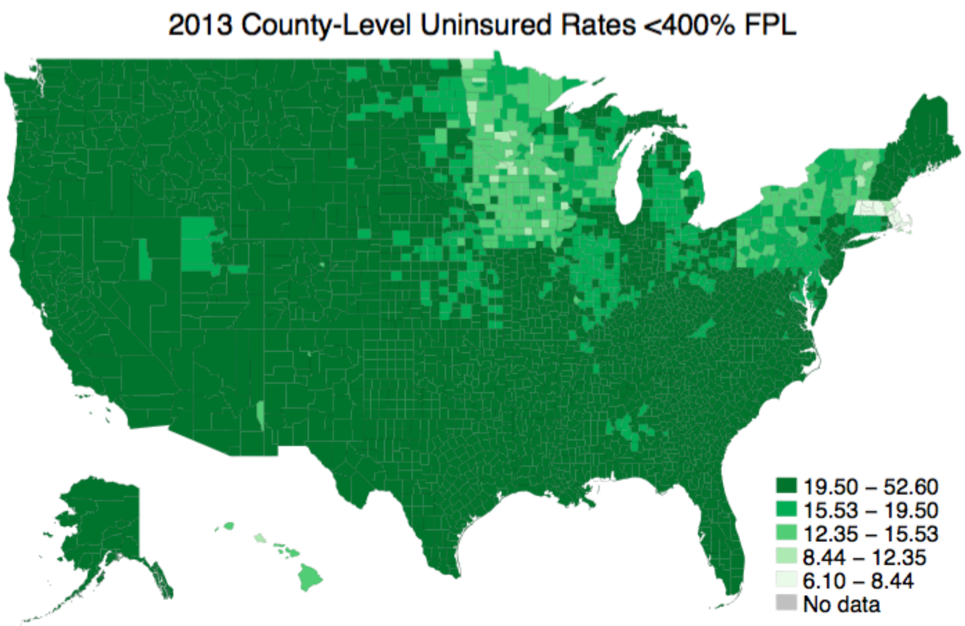
(b) 2016



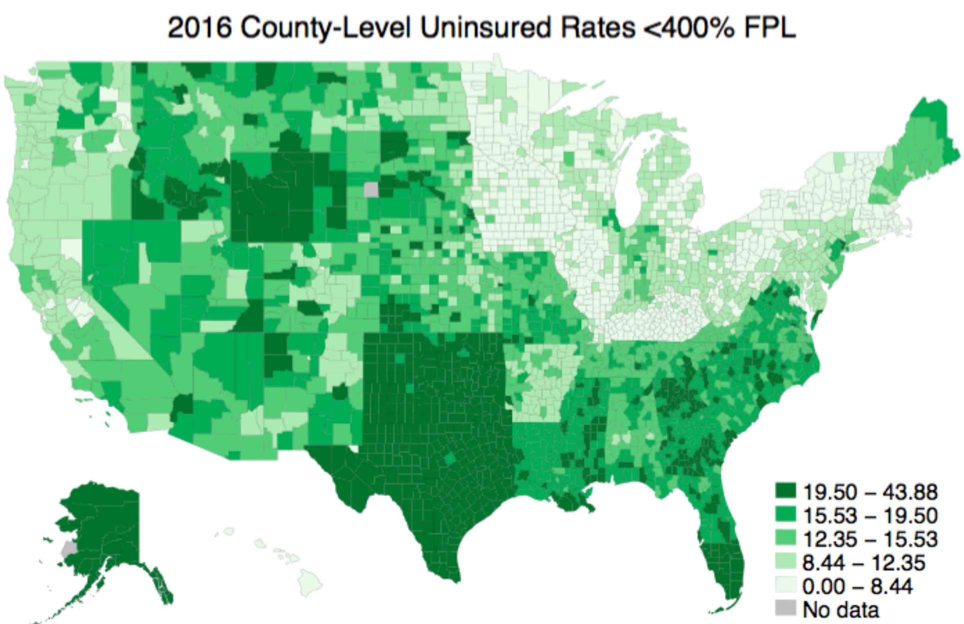
Notes: Bins indicate 2016 quintiles.
Source: Census Small Area Health Insurance Estimates

Figure 16: 2013 & 2016 County-Level Uninsured Rates <400% Federal Poverty Line

(a) 2013



(b) 2016



Notes: Bins indicate 2016 quintiles.
Source: Census Small Area Health Insurance Estimates

B Synthetic Control Model

As a robustness check for my main regression methodology, I use a synthetic control model as established in Abadie et al. [2010]. In this model, I combine expansion states to form a single treatment observation and I use non-expansion states to create a synthetic counterfactual. I use state-level data by collapsing my county data weighting by total population. I omit data from all mid-year expansion states in order to keep a consistent treatment period. I also drop unbalanced observations.

The model constructs a counterfactual of treated states' combined eviction rate to estimate whether Medicaid expansion changed the treated states' actual eviction rates. The model constructs a counterfactual by determining how treated states can be thought of as a composition of similar states given certain predictor variables and estimating how much these predictor variables account for post-treatment eviction rates. This model maximizes these weighted averages based on predictor variables to create the most accurate counterfactual. Then, one can use a difference-in-differences approach to estimate if the treatment caused a change between the actual treated states' post-treatment eviction rate and their synthetic control's.

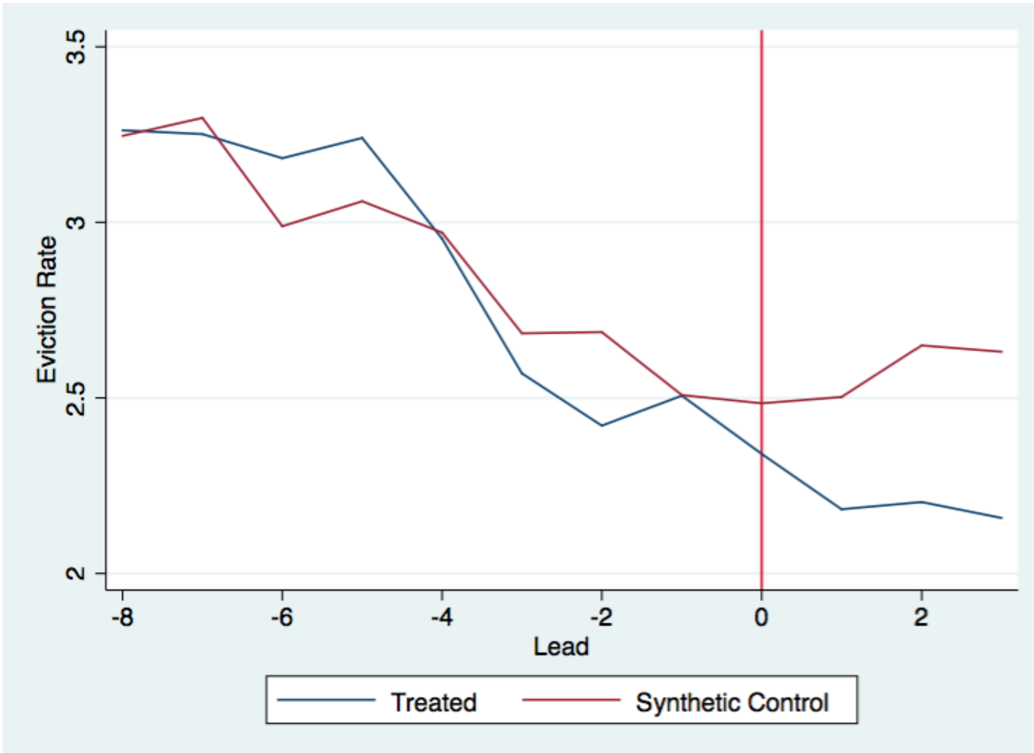
In my model, I rely on three predictor variables. First, I use annual state-level eviction rates for each year from 2006 to 2011 with the assumption that prior year eviction rates are accurate predictors for a location's future eviction rates. Second, I use a state's pre-2013 average of median rent as percent of income. I include this predictor based on literature suggesting that rent burden is a cause of eviction

[Desmond, 2012]. Third, I use a state's pre-2013 average percent of population that is African-American because prior literature suggestions African-American households are disproportionately affected by eviction [Desmond, 2016].

Figure 17 illustrates the results of the synthetic control model. Using 16 states in the treatment group and 17 states to generate the synthetic control group, the pre-treatment trends fail to align perfectly. As is, the model suggests that that the Medicaid expansion decreased eviction rates by about 0.4 evictions per 100 renting households. This translate to nearly a 20% decrease in the eviction rate. I illustrate the treatment effect in Figure 18, which suggests that the impact of the expansion on eviction rates increases over time. Figure 19 illustrates p-values of the synthetic control model estimates. The probability the 2014 estimate would happen by chance is less than 10% and the probability the 2015 and 2016 estimates would happen by chance are just over 2%.

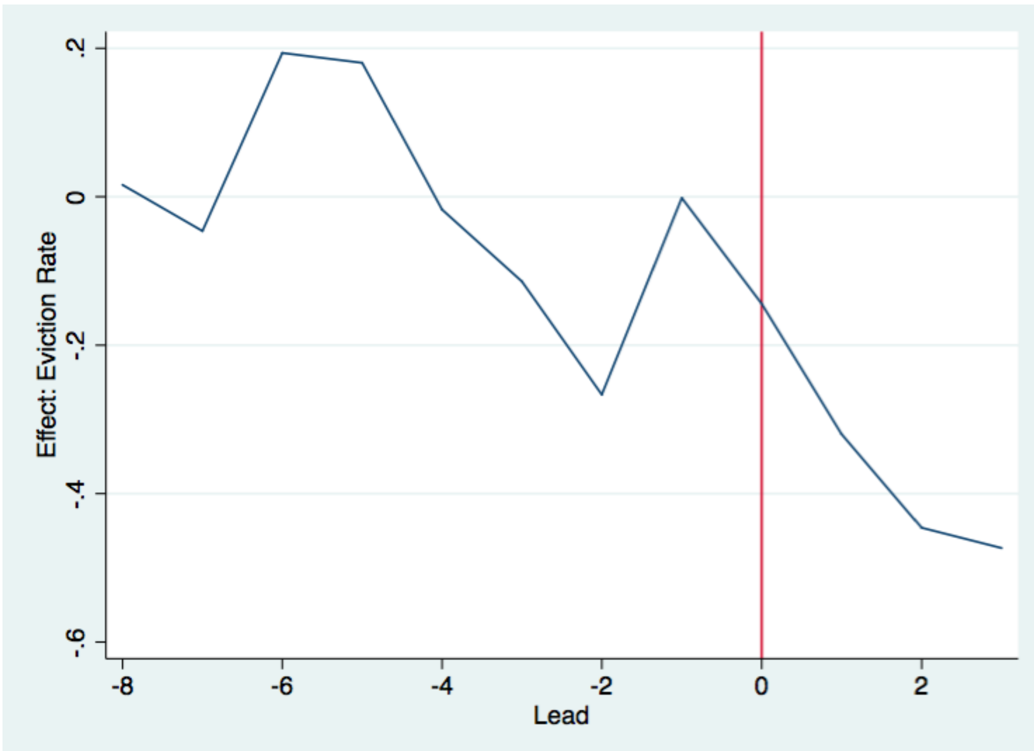
Although these results lack complete validity because of the misalignment between the pre-2014 treatment and synthetic control trends, the point estimates continue to suggest Medicaid expansion had a negative impact on eviction rates. The estimate from the synthetic control model is larger in magnitude than many of my DD models and notably uses more limited data as I drop mid-year expansion states and unbalanced counties. This methodology adds robustness to my regression methodology as it relies on a permutation-based approach to inference rather than the standard errors. The synthetic control methodology and its permutation-based approach to inference provides additional support for the interpretation that expansions did indeed reduce eviction rates.

Figure 17: Synthetic Control Model



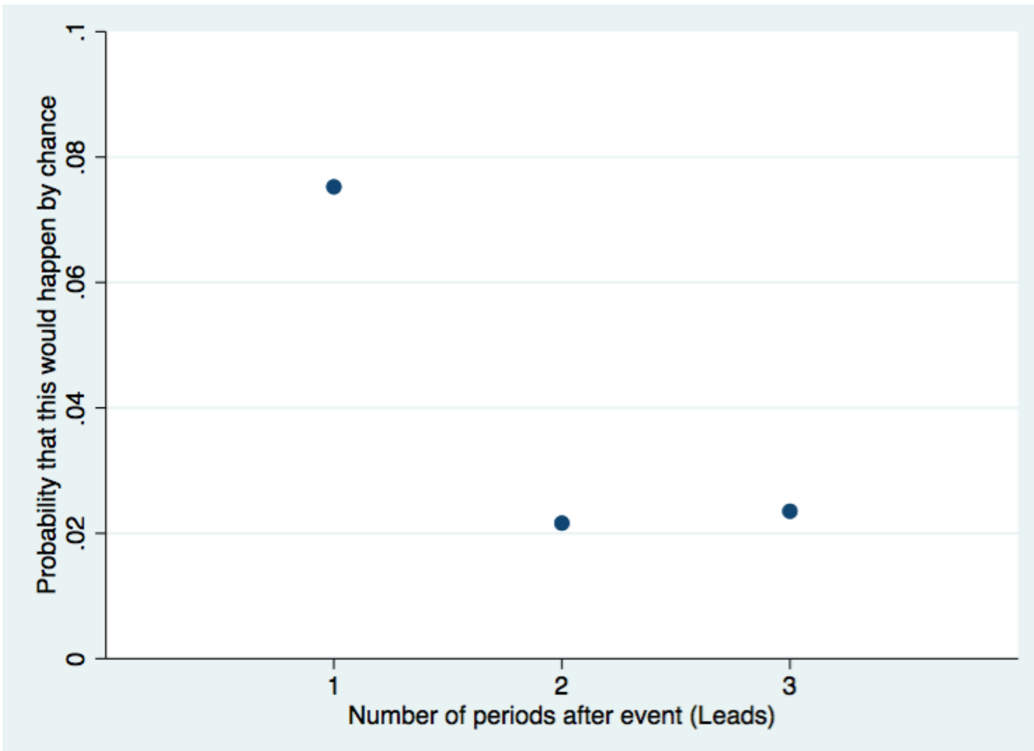
Notes: Treated states include those that expanded in January 2014. The synthetic control is constructed using data from non-expansion states. Predictor variables for the synthetic control include pre-2013 mean county median rent as percent of income, pre-2013 average African-American percentage of a county population, and annual eviction rates from 2006-2011. Eviction data from states with varying levels of data collection across time are excluded. These dropped data are from Washington D.C. in 2005, Maine in 2005-2006, New Hampshire in 2015-2016, New York in 2007-2016, Rhode Island in 2005-2007 and 2013-2014, South Carolina in 2005-2008 and 2016, New Jersey in 2005 and 2016, West Virginia in 2005-2006, Massachusetts in 2005-2007, and all Pennsylvania data.
Sources: The Eviction Lab, The American Community Survey 5-Year Estimates, The 2010 Census

Figure 18: Synthetic Control Model - Treatment Effect



Notes: Treated states include those that expanded in January 2014. The synthetic control is constructed using data from non-expansion states. Predictor variables for the synthetic control include pre-2013 mean county median rent as percent of income, pre-2013 average African-American percentage of a county population, and annual eviction rates from 2006-2011. Eviction data from states with varying levels of data collection across time are excluded. These dropped data are from Washington D.C. in 2005, Maine in 2005-2006, New Hampshire in 2015-2016, New York in 2007-2016, Rhode Island in 2005-2007 and 2013-2014, South Carolina in 2005-2008 and 2016, New Jersey in 2005 and 2016, West Virginia in 2005-2006, Massachusetts in 2005-2007, and all Pennsylvania data.
Sources: The Eviction Lab, The American Community Survey 5-Year Estimates, The 2010 Census

Figure 19: Synthetic Control Model - Post-Treatment Estimates P-Values



Notes: Treated states include those that expanded in January 2014. The synthetic control is constructed using data from non-expansion states. Predictor variables for the synthetic control include pre-2013 mean county median rent as percent of income, pre-2013 average African-American percentage of a county population, and annual eviction rates from 2006-2011. Eviction data from states with varying levels of data collection across time are excluded. These dropped data are from Washington D.C. in 2005, Maine in 2005-2006, New Hampshire in 2015-2016, New York in 2007-2016, Rhode Island in 2005-2007 and 2013-2014, South Carolina in 2005-2008 and 2016, New Jersey in 2005 and 2016, West Virginia in 2005-2006, Massachusetts in 2005-2007, and all Pennsylvania data.
Sources: The Eviction Lab, The American Community Survey 5-Year Estimates, The 2010 Census

C Optimal Health Insurance Benefit Rate

If eviction rates respond to health insurance coverage, the optimal health insurance benefit rate model theorized by Baily [1978] and Chetty [2005] can be altered to account for this relationship. As I estimate in my regression analysis, the elasticity between eviction rates and the uninsured rate is negative. Consequently, one would assume that the optimal health insurance benefit rate should be higher than that predicted without this relationship. To estimate the impact of this elasticity, I follow the same model as Gross and Notowidigdo [2011]. I treat eviction as analogous to bankruptcy. An individual facing bankruptcy faces an initial debt payment, much of which is relieved by the government. I assume that an individual facing a formal eviction faces an initial money judgment, often including back-owed rent, although much of this cost is also relieved because the individual faces the eviction rather than paying a money judgment. I assume that the individual still faces some cost due to the eviction. This could be due to a loss of personal objects, moving costs, and potential negative impacts on the individual's labor supply. I also assume that in this scenario an individual becomes eligible for increased welfare, in which case the government bears a cost from the eviction filing.

As with bankruptcy outlined in Gross and Notowidigdo [2011], an individual faces two shocks from an eviction: a health shock and a productivity shock. The probability of a health shock is p_H in which an individual would utilize m units of medical care at the price 1 - b_H, where b_H is the coinsurance provided by the government. The value of medical consumption is assumed to be a concave function, $v(m)$. The probability shock, $p_B(e, m)$, is a function of an individual's effort to avoid an eviction. Analogous with bankruptcy, I assume effort follows a convex function $f(e)$ as an individual would likely have to make significant sacrifices, such as cutting back on food spending or other necessities, to avoid a likely eviction notice. Furthermore, I assume that if an individual faces an eviction filing, she has to pay some price ϵ; however, if the individual is evicted, then she only pays a fraction of that cost, 1-b_E. The term b_E allows for the assumption that an eviction still results in a cost to the individual despite not paying a money judgment and that the government will also face a cost.

A social planner can impost a lump-sum tax, τ, in the four states of the world for this individual. With no shocks, the individuals consumption, c, will be a function of her wealth, W, and the tax: $c = W - \tau$. With just a health shock, her consumption will be: $c_H = W - \tau - (1 - b_H)m$. With just a productivity shock, her consumption will be: $c_E = W - \tau - (1 - b_E)\epsilon$. With both shocks, her consumption becomes: $c_E = W - \tau - (1 - b_H)m - (1 - b_E)\epsilon$. In this conditions, the individual solves:

$$V * (b_H, b_E, \tau) \equiv max_{m,e} p_H p_E(e, m)(u(c_H E) + v(m)) + (1 - p_H)p_E(e, m)u(c_B)$$
$$+ p_H(1 - p_E(e, m))(u(c_H) + v(m)) + (1 - p_H)(1 - p_B(e, m))u(c) - f(e)$$

A social planner maximizes $V*$ under the resource constraint $\tau = p_H b_H m + p_E(e, m)b_E\epsilon$. Optimal health insurance benefits then must satisfy:

$$\frac{p_E u'(c_H E) + (1 - p_E)u'(c_H)}{\overline{u}'} = 1 + \frac{dlogm}{dlogb_H} + \frac{p_E b_E \epsilon}{p_H b_H m} * \frac{dlogp_E}{dlogb_H}$$

where $\overline{u}'$ is an individual's expected marginal utility of consumption. This is the same equation derived by Gross and Notowidigdo [2011] adjusted for eviction rather than bankruptcy. Previous literature has estimated the price elasticity of health consumption. In this paper, I rely on the main specification from my DD model from which I estimate then that expanding Medicaid eligibility by 38 percentage points reduces eviction rates by 12.5%. As I estimate a negative elasticity, the optimal health insurance benefit rate would be higher than in standard calculations.

Solving for the optimal health insurance benefit rate using the eviction elasticity proves challenging because of an inability to provide estimates for b_E and an estimate for p_E. Nevertheless, one can assume that both of these are non-zero values. The government likely bears a cost, such as increased welfare eligibility and receipt, for an individual facing an eviction filing. An individual certainly still faces a cost from an eviction, even if she does not pay the court money judgment. It is unlikely that the government and the individual's costs amount to ϵ as would be the case for bankruptcy; however, this cost division still provides a beneficial theoretical framework.

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