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HEALTHCARE AND HOUSING:
ANALYZING THE AFFORDABLE CARE ACT'S IMPACT ON EVICTION RATES

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ABSTRACT

I use formal eviction records and demographic data to quantify the impact of federally subsidized Medicaid insurance on county level eviction rates. In 2014, the Affordable Care Act (ACA) gave states the choice to expand Medicaid to a low-income and previously ineligible segment of the population. In providing insurance against health shocks, ACA expansion may reduce the prevalence of adverse financial shocks that lead to eviction. I use this policy to create a quasi-natural research design in which expansionary status determines treatment and control groups. Using a difference in difference estimation technique, I estimate that ACA expansion led to an average 10% decrease in yearly eviction rates between 2014 and 2016. Had all states expanded ACA Medicaid in 2014, I estimate that policy would have prevented a total of 283,360 evictions between that year and 2016. My analysis is particularly interesting for policy makers as it presents unintended benefits of the ACA. It adds academic value to the existing health insurance literature and is a strong addition to the currently limited but burgeoning field of eviction research.

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Chapter 1

Introduction

My research seeks to estimate the causal impact of Affordable Care Act (ACA) Medicaid expansion on eviction rates. In 2014, the Affordable Care Act expanded Medicaid eligibility requirements to include a larger, previously uncovered segment of the population. Through the Affordable Care Act, an individual's income determines eligibility and adults under 65 with incomes at or below 138% Federal Poverty Line (FPL) now qualify.[1] Prior to this change, Medicaid was only offered to disabled adults and eligible families that met income standards determined by the Aid to Families with Dependent Children (AFDC) program. This meant that low-income, non-elderly, nondisabled adults who did not have dependent children were left in a coverage gap.

However, ACA Medicaid expansion is not a nationwide mandate. This an opt-in policy decided by each state, which means new eligibility requirements only apply to those that expand. In my research, I exploit the policy variation that exists across states and use a difference in difference (DID) design to estimate the causal impact of ACA Medicaid expansion on county eviction rates. DID allows my model to estimate the causal impact of policy by comparing changes in eviction rates for expansion counties against changes in eviction rates for non-expansion counties. I hypothesize that by providing insurance against health shocks, ACA expansion may reduce the prevalence of adverse financial shocks that lead to eviction. This mechanism appears even more viable when considering those targeted by ACA expansion.

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[1] For 2020: 100% FPL is $12,2760 for individuals and $26,200 for a family of 4 (Federal Poverty Line (FPL))

Low-income, uninsured adults are vulnerable to high out-of-pocket health care costs and medical debt.[2] Additionally, in the last 30 years America has encountered an affordable housing crisis that disproportionately affects the poor. As affordable housing becomes scarce and median rents increase, rental payments consume higher percentages of household income.[3] In 2013, 1 in 8 poor renting families were unable to pay all of their rent (Desmond, 2016). This means that low-income Americans, ACA's target population, are particularly vulnerable to eviction. By preventing health shocks from becoming serious financial shocks, Medicaid may better protect the poor against eviction.

Many papers have drawn conclusions between Medicaid adoption and improved financial outcomes. The most relevant paper to my study is Gallagher et al. (2018), which estimates the impact of ACA Marketplace subsidies on home delinquency payments. However, the current literature does not contain any papers focused specifically on ACA Medicaid expansion and eviction rates.[4]

[2] See Finkelstein et al. (2012), Hu et. al. (2018), Miller et al. (2018) and Brevoort et al. (2017).
[3] See La Jeunesse et al. (2019) and Downs (2008).
[4] Based on my literature review

Chapter 2

Literature Review

In this paper, I propose a mechanism through which ACA expansion works to reduce eviction rates. I posit that in providing insurance against health shocks, ACA expansion may reduce the prevalence of adverse financial shocks that lead to eviction. I structure my literature review in the following way to support this hypothesis: I begin by reviewing existing literature that identifies the financial benefits of Medicaid. I then provide evidence as to why Medicaid helps prevents a specific financial consequence like eviction. I argue that under new ACA eligibility standards, Medicaid coverage will expand insurance, and its financial benefits, to a segment of the population that is most at risk of eviction.

The Financial Benefits of Medicaid Coverage

Medicaid coverage provides direct financial benefits by reducing out-of-pocket costs and protecting against unpaid bills. Finkelstein et al. (2012) observes individual-level gains derived from Medicaid.[5] The research design exploited a state-sanctioned Medicaid lottery in Oregon that offered insurance to low-income, uninsured adults. Those who were randomly selected, offered Medicaid, and enrolled experienced a, “35 percent decline in having any out-of-pocket medical expenditures” (Finkelstein et al., 2012, p. 1061). Furthermore, insurance led to a, “25 percent decline in the probability of having an unpaid medical bill sent to a collection agency” (Finkelstein et al., 2012, p. 1061). Hu et. al. (2018) finds that Medicaid expansion led to a,

[5] Took place in 2008, prior to the 2014 ACA Medicaid rollout

"substantial decline in the amount of balances in collection in the treated states relative to the synthetic control unit" (p.104). They estimate a $1140 reduction in collection balances for those who gain Medicaid coverage through the ACA. Unfortunately, data limitations prevented the authors from distinguishing medical collections from non-medical collections. Miller et al. (2018) uses individually linked insurance and credit data to give a more precise estimate. They find that Medicaid adoption, through the Healthy Michigan Project, reduced the amount of medical debt in collections by over 50% (relative to the pre-ACA mean). Finally, Brevoort et al. (2017) estimates that between the beginning of 2014 and the end of 2016, ACA Medicaid expansion led to an aggregate reduction of $5.89 billion of medical debt. This includes debt owed to banks and third-party collection agencies.

By reducing medical and non-medical debt, it appears that Medicaid coverage provides a mechanism to prevent medical expenses and shocks from becoming serious financial burdens. I now look to determine how these financial benefits can offer new Medicaid enrollees protection against eviction.

Mechanism by which ACA Expansion Protects Against Evictions

Prior to ACA expansion, Medicaid was offered to disabled adults and eligible families that met income standards determined by the Aid to Families with Dependent Children (AFDC) program. Now, in ACA expansion states, Medicaid is offered to non-elderly adults with income at or below 138% FPL. Therefore, income level is the primary factor that determines eligibility.

State and national studies provide further description of these newly eligible Medicaid enrollees. Miller et al. (2018) provides a state level perspective through an analysis of the

Healthy Michigan Program, a slightly modified version of traditional ACA Medicaid rollout. At enrollment, the full sample had an average household income of 39% FPL.[6] In Miller and Wherry (2017), the authors conducted a national survey on Medicaid-eligible adults, capturing baseline statistics prior to the 2014 ACA Medicaid rollout. Roughly 1/3 had problems paying, or were unable to pay, medical bills in the past 12 months. An even larger portion, roughly 2/3, worried about their ability to pay medical bills.

Hu et al. (2018) provides context for these medical bill troubles by noting that the "annual cost of inpatient care for a person aged 18 to 64 who was hospitalized was approximately $15,000" (p. 99). Dobkin et al. (2018) finds that following a hospitalization, the uninsured non-elderly face an increase in probability of bankruptcy that is 3 times greater than that of the insured non-elderly.[7] These studies showcase that hospitalizations and unexpected medical shocks can produce significant expenses for uninsured, non-elderly households. So much so that Finkelstein et al. (2012) and Hamel et. al (2016) find that medical bills led the uninsured to skip payments on other bills and made it difficult to pay for necessities like food, heat, or housing.[8] This can increase a household's chance of eviction as Desmond, Gershenson, and Kiviat (2015) finds that most evictions come from nonpayment of rent (as cited in Desmond & Kimbro, 2015).

However, medical expenses aren't the only costs that might lead ACA eligible individuals towards eviction. In Desmond et al. (2015), the authors find that the majority of poor

[6] Enrollees met the <= 138% FPL income standards, were previously uninsured, and had not been enrolled in other state benefit programs prior to enrolling in HMP

[7] The increased probability of bankruptcy is 1.4 percentage points and 0.4 percentage points for the uninsured and the insured, respectively.

[8] "Over a third in each group (34 percent of the insured and 39 percent of the uninsured) say they were unable to pay for basic necessities like food, heat, or housing as a result of medical bills." (Hamel)

renting families spend more than 50% of their income on housing costs. This reflects a larger U.S. housing trend which has shown an increase in monthly rents and a decrease in affordable housing options. La Jeunesse et al. (2019) notes that between 1990 and 2017, America's affordable rental stock dropped by 4 million units.[9] At about the same time, from 1990 to 2006, the median asking monthly rent increased by 70 percent (Downs, 2008). This is exacerbated by reports from the U.S. Census Bureau's Current Population Survey (1990–2012) which shows slow median income growth for families headed by individuals with less than a college degree (as cited in Desmond, 2015).[10]

Under ACA expansion, income at or below 138% FPL now determines Medicaid eligibility in expansion states. Therefore, the housing and health care problems facing low-income Americans are likely shared by those new enrollees. This leads to the assumption that newly eligible Medicaid enrollees would also be vulnerable to eviction.

Through my hypothesis, I propose that ACA expansion can reduce the prevalence of adverse financial shocks that lead to eviction. Gallagher et al. (2018) examines this relationship by studying the impact of ACA Marketplace subsidies on home delinquency payments. Although ACA Marketplace subsidies are not the same as ACA Medicaid expansion, this paper is particularly important because it directly connects ACA policy to housing outcomes.[11] The authors find that uninsured households that qualify for subsidized Marketplace insurance experience a 25 percent drop in the rate of home delinquency. The authors reason that health

[9] eclipse the HUD defined standard for "affordable dwellings"; housing which accounts for 30% of household income.

[10] 6% growth for households headed by individuals with a ninth-grade education or less, and 7.3% growth for those with only a high school diploma

[11] ACA Marketplace subsidies are available in all U.S. states and provide subsidized health care premiums for households earning between 100-400% FPL and subsidized out-of-pocket expenses for households earning between 100-250% FPL.

insurance, “appears to prevent health shocks from becoming significant liquidity shocks and, thereby, reduces the probability of home delinquency” (p. 69). Delinquent payments on mortgages and rent are precursors to foreclosures and evictions. This study largely influenced my own research and provides compelling evidence that ACA policy can lead to improved housing outcomes for enrollees.

Chapter 3
Data

Data Characteristics and Sourcing

My data come from The Eviction Lab at Princeton University, a research team that has created the nation's first database on evictions. The dataset includes demographic statistics and eviction statistics recorded at the county-level for all 50 states and Washington DC. The dataset spans 2000-2016 and observations are denoted at the county, year level. Key demographic statistics include population, poverty rate, median household income, median gross rent, and rent burden, which measures median gross rent as a percentage of household income. These statistics come from the 2000 and 2010 Censuses and 5-year estimates from the 2009, 2012, and 2015 American Community Surveys.

Key eviction statistics include eviction filings, eviction judgements, and eviction rates. The Eviction Lab team underwent an intensive data collection process, collecting over 80 million court records, to produce these statistics. Court records came from state and county clerks as well as two private data companies, LexisNexis Risk Solutions and American Information Research Services. The original data came as both individual-level, court-ordered eviction records and aggregate, county-level records. The data was then geocoded, matching tenant addresses to counties and states. I match this data to the time of Medicaid expansion, dividing counties into treatment and control groups based on their expansionary status in 2014.

My analysis includes 41,339 observations out of a dataset total of 53,437.[12] Observations without eviction rate statistics were dropped. Included counties represent 78.35% of the total United States population. All states except Alaska, Arkansas, South Dakota, North Dakota were included in my analysis.[13] Furthermore, the Eviction Lab dataset does not account for informal evictions, which occur outside of court and are negotiated between landlord and tenant. According to Desmond and Shollenberger (2015), results from a 2009-2011 survey on Milwaukee renters found that informal evictions occurred at twice the rate of formal court ordered evictions. This figure is specific to Milwaukee, but it suggests that my dataset captures only a portion of all annual evictions. My analysis suggests causality between ACA expansion and reduced formal eviction rates. If populations facing formal and informal evictions are equivalent, it is then reasonable to assume that ACA policy would reduce informal eviction rates through the same mechanisms.

[12] 612 observations have imputed eviction rates, which I included
[13] These states did not have consistent data coverage for 2000-2016.

Chapter 4

Methodology

Two-Group, Two-Period DID Structure

I chose to use a difference in difference (DID) research design to estimate the causal impact of ACA Medicaid expansion on county level eviction rates. DID creates a quasi-natural research design by exploiting policy variation across observations to assign treatment and control groups (Besley and Case, 2000). ACA policy lends itself well to analysis under this design. The year 2014, the year in which states could begin choosing to expand Medicaid coverage, creates clear boundaries for pre-treatment and post-treatment time periods. Additionally, the policy allows states to self-select into treatment (expansion states) or control (non-expansion states) groups. The simplest DID structure includes two groups and two time periods (‘2x2’). In my work, the treatment group includes counties from states that expanded ACA coverage in 2014 ($T_g=1$), while the control group accounts for all else ($T_g=0$). Additionally, observations are divided into two time periods: pre-treatment, 2000-2013 ($P_t=0$) and post-treatment, 2014-2016 ($P_t=1$). Therefore, allow an interaction term $D_{g,t} = T_g * P_t$, where $D_{g,t} = 1$ if group g receives treatment in time period t, and $D_{g,t} = 0$ if group g encounters control conditions in time period t (Wing, Simon, Bello-Gomez, 2018).

Ideally, we would measure ACA’s causal impact on eviction rates by estimating the average change in evictions with: $Y(1)_{g,t} – Y(0)_{g,t}$, where $Y(1)_{g,t}$ represents the outcome for group g in period t under treatment conditions, and $Y(0)_{g,t}$ represents the outcome for the same g and t under control conditions. However, this is not possible because groups cannot change their treatment/control status within the same time period.

Instead we observe:

$Y_{g,t} = Y(0)_{g,t} + [Y(1)_{g,t} – Y(0)_{g,t}]\, D_{g,t}$ (1) (Wing, Simon, Bello-Gomez,2018)

For control group counties: $Y_{g,t} = Y(0)_{g,t}$ because $D_{g,t} = 0$

For treatment counties: $Y_{g,t} = Y(1)_{g,t}$ because $D_{g,t} = 1$

The Parallel Trends Assumption

We must include assumptions that establish a counterfactual case to allow for the estimation of $Y(1)_{g,t} – Y(0)_{g,t..}$. We must assume that in the absence of ACA Medicaid policy, eviction rates ($Y(0)_{g,t}$) are “determined by the sum of a time-invariant state effect and a year effect that is common across states” (Angrist and Pischke, 2013, p. 229). In my research, the word “state” represents the two types of counties: expansionary counties ($T_g=1$), and non-expansionary counties ($T_g=0$). Shown mathematically, the assumption appears:

$E\,[Y_{0,g,t} \mid g, t] = \alpha_g + \lambda_t$ (2) (Angrist and Pischke, 2013, p. 229)

Here (α_g) represents the time-invariant group effect and (λ_t) represents the year effect common across groups. Despite each group having initial differences in eviction rates (α_g), we assume that the trend behavior for eviction rates (λ_t) is identical in treatment and control groups (Angrist and Pischke 230). This is the parallel trends assumption, which is critical for estimating the causal impact of ACA policy on eviction rates. Under the parallel trends assumption, ACA policy, or treatment, “induces a deviation from this common trend” (Angrist and Pischke 230). Denoting the treatment effect (γ), observed eviction rates, $Y_{g,t}$, are written:

$Y_{g,t} = \alpha_g + \lambda_t + \gamma D_{g,t} + \varepsilon_{g,t}$ (3) (Angrist and Pischke, 2013, p. 229)

As previously described, the interaction term $D_{g,t} = 1$ for treatment counties in the post-treatment period. Therefore, the treatment effect (γ) will only influence eviction rates for expansionary counties in years 2014-2016. Under the parallel trends assumption, the coefficient (γ) is the average, yearly difference between actual county level eviction rates (policy present) and counterfactual rates (policy absent).

$$(\gamma) = E\,[Y_{1g,t} - Y_{0g,t} \mid g, t] \quad (4) \quad \text{(Angrist and Pischke, 2013, p. 229)}$$

$$(\gamma) = \left[E\left(Y \mid T_g = 1, P_t = 1\right) - E\left(Y \mid T_g = 1, P_t = 0\right)\right] - \left[E\left(Y \mid T_g = 0, P_t = 1\right) - E\left(Y \mid T_g = 0, P_t = 0\right)\right] \quad (4.1)$$

The value of (γ) estimates that for counties in the post-treatment period, eviction rates are (γ) percentage points different from what they would have been, absent of policy. The following graphic illustrates the equation $Y_{g,t} = \alpha_g + \lambda_t + \gamma D_{g,t} + \varepsilon_{g,t}$[14]

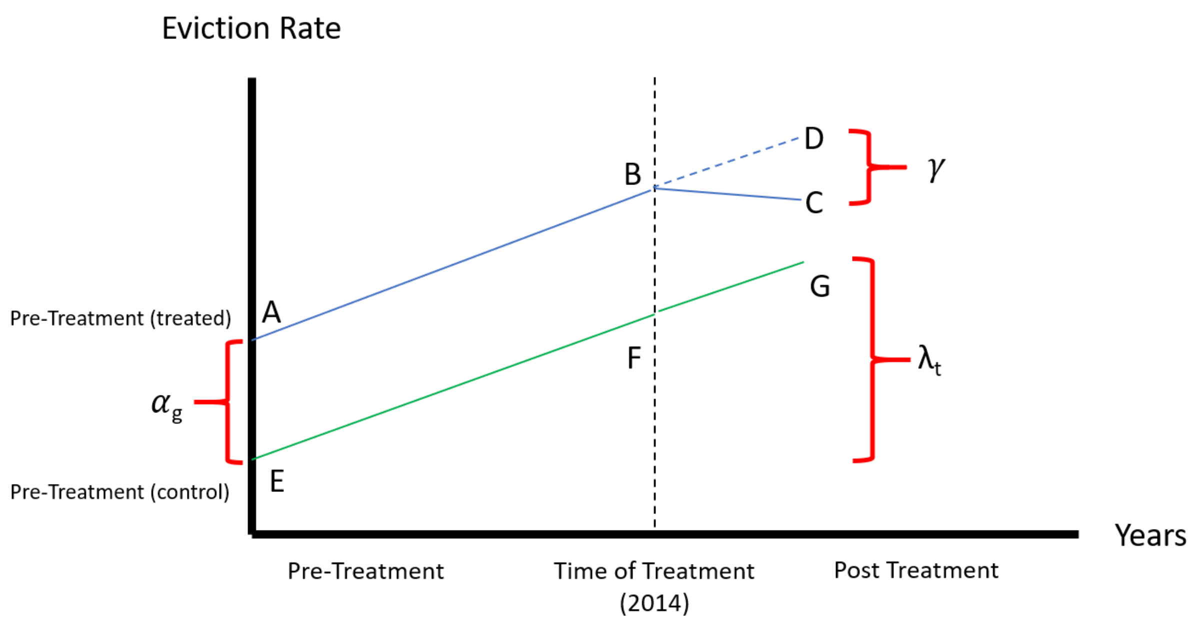


Figure 1. Two-Group, Two-Period DID Graph

[14] This graph is not derived from my actual data.

Graphically, line segments AB and EF exhibit pre-treatment parallel trends in eviction rates. Line B-D represents the time constant trend that would have followed in the treatment group, absent of policy. This is the counterfactual case. Line B-C represents the actual trend for the treatment group.

De-Aggregating with Two-Way Fixed Effects

The previous example presents a 'two-group, two-period' DID structure that is useful for understanding the model's basic mechanics. However, adding two-way fixed effects allows us to control for more variation among groups and across time. Two-way fixed effects control for unmeasured variables that influence eviction rate changes across counties and years (Wing, Simon, Bello-Gomez, 2018). "The DID design is meant to control for these unmeasured confounders even though the underlying variables are not measured explicitly" (Wing, Simon, Bello-Gomez, 2018). Controlling for these unmeasured variables is essential for preventing omitted variable bias.[15] The term two-way fixed effects refers to location fixed effects and time fixed effects. Location fixed effects disaggregate the broader 'treatment' and 'control' groups, *g*, into individual counties, *i*. Time fixed effects disaggregate the broader 'pre-treatment' and 'post-treatment' time periods into individual years. We apply the same parallel trends assumptions and assume that, "any unmeasured determinants of the outcomes are either time invariant or group invariant" (Wing, Simon, Bello-Gomez, 2018). This allows us to construct counterfactual cases and estimate the treatment effect in individual treatment counties.

[15] This will be discussed later when considering the model's strict exogeneity assumption and methodology for addressing policy endogeneity.

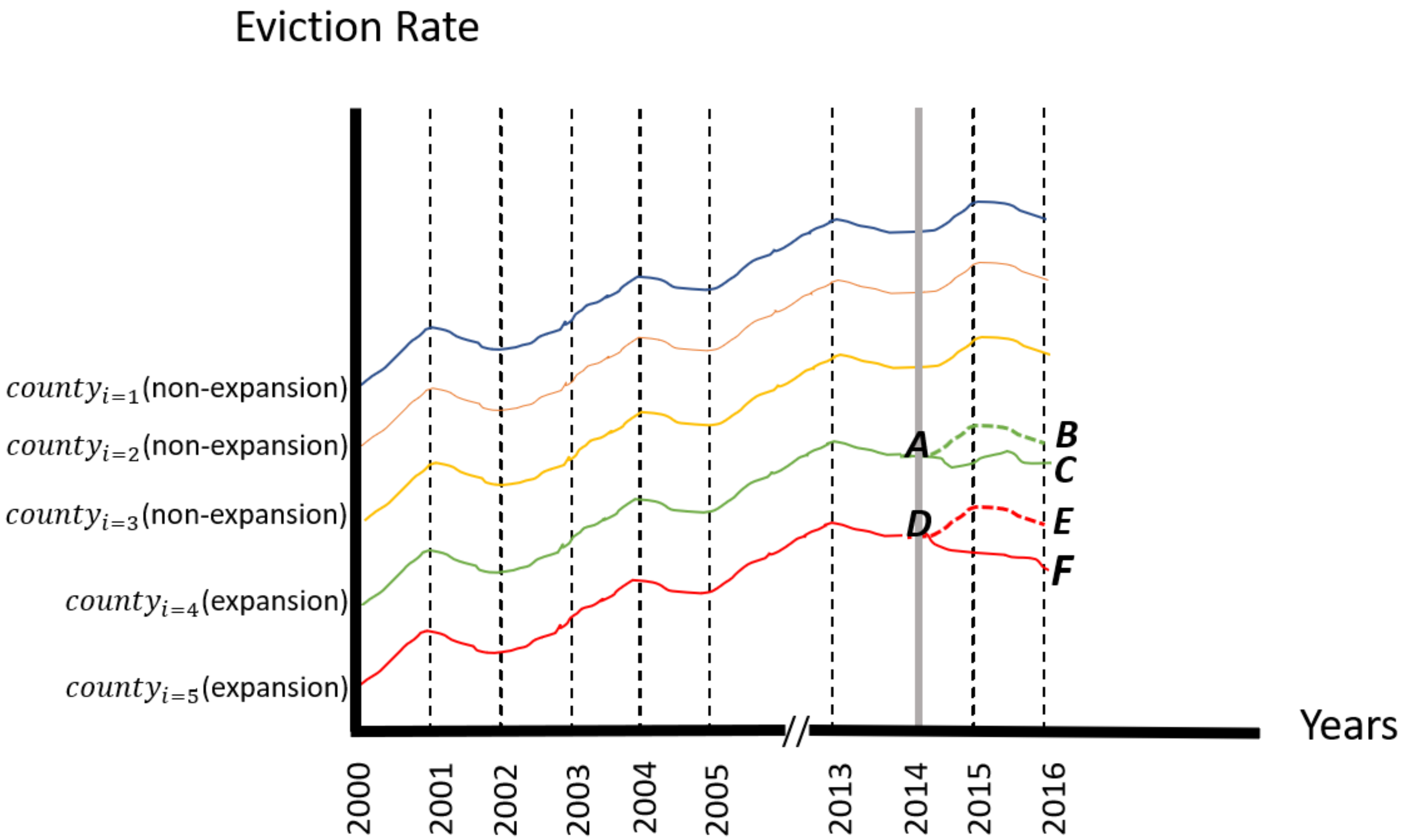


Figure 2. Two-Way FIxed Effects Graph

*ACA Medicaid expansion occurs in 2014.

*2000-2013 constitutes pre-treatment; 2014-2106 constitutes post-treatment

*Eviction rate trends for control counties are all equal; leveling comes from county differences

The new model follows: $Y_{i,t} = \alpha_i + \lambda_t\theta_t + \delta x_{it} + \gamma D_{i,t} + \varepsilon_{i,t}$ (3.1)

α_i: Location fixed effects (one for each county)

θ_t: Vector of time fixed effects dummies (one for each year 2000-2016)

x_{it}: Vector of measured, time-varying, county-level covariates[16]

$D_{i,t}$: Interaction term ($D_{i,t} = T_i * P_t$)[17]

α_i accounts for unmeasured, county level characteristics that uniquely influence eviction rates in each county *i*. The previous graph had only two intercepts, one showing initial eviction rates for the aggregated treatment group and the other representing initial rates for the control group. α_i allows for differentiation between all counties, and the new graph presents intercepts for each county$_i$, $\{i = 1, \ldots, N\}$. Under assumption, the impact of α_i on $Y_{i,t}$ does not change over time; therefore, the mean ($\bar{\alpha}_i$) is equivalent to α_i for each county. Using a demeaning technique, it is possible to control for these unmeasured, county specific covariates by eliminating them from the model. After demeaning, α_i, "will have a value of 0 for every case, and since they are constants they will drop out of any further analysis" (Williams, 2018).

The coefficient (λ_t) estimates the average change in eviction rates between a base year and each year 2000-2016. This is a departure from the previous λ_t coefficient, which was used in the 'two-group, two-period' structure to estimate the average change in eviction rates between the pre and post treatment periods. Time fixed effects allow for, "flexible time trends that move

[16] This includes: poverty rate, median household income, median gross rent, rent burden ("Median gross rent as a percentage of household income"), median property value, pct. renter occupied housing, pct. White (Non-Hispanic or Latino), pct. African American, pct. Hispanic

[17] T_i *= 0 (non-treatment county), 1 (treatment county);* P_t *= 0 (pre-treatment years 2000-2013), 1 (post-treatment years 2014-2016)*

up or down from period to period" (Wing, Simon, Bello-Gomez, 2018). Here, 'period to period' is year to year. Under parallel trends, we still assume that time trends influence all groups equally. Therefore, eviction rate time trends will move in parallel for all groups. However, the model can now control for more acute macroeconomic shocks that influence eviction rates from year to year.

With the addition of two-way fixed effects, the interpretation of coefficient (γ) remains the same. Under assumption, graphical segments AB and DE represent the counterfactual eviction rate trends for county$_{i=4}$ and county$_{i=5}$, which are equal to the control trends (counties$_{i=1\text{-}3}$). Graphically, segments AC and DF show the actual, ACA influenced eviction rate trends for county$_{i=4}$ and county$_{i=5}$ respectively. The county level treatment effect for county$_{i=4}$ is the difference between BC. However, the treatment effect for county$_{i=5}$ (difference between EF) is different than that in county$_{i=4}$. Therefore, (γ) is the average of all individual county treatment effects.

Exogeneity Assumption: Addressing Policy Endogeneity

In 2014, states independently chose whether to expand or decline ACA Medicaid. Besley and Case (2000) argues that, "[i]f state policy making is purposeful action, responsive to economic and political conditions within the state, then it may be necessary to identify and control for the forces that lead policies to change". To avoid omitted variable bias, an empirical model that directly includes an observation's policy decision must also control for the variables that influence this choice. In my model, that policy decision is reflected in the interaction term $D_{i,t}$, which directly address each county's expansionary status across time. Therefore, we assume that expansionary status is randomly assigned, conditional on observed covariates x_{it} and the two-way effects α_i and θ_t. (Wing, Simon, Bello-Gomez, 2018) represent this exogeneity assumption with the following equation:

$$\mathrm{E}[Y(j)_{i,t}|\alpha_i, \theta_t, x_{it}, D_{i,1}, \ldots D_{i,T}] = \mathrm{E}[Y(j)_{i,t}|\alpha_i, \theta_t, x_{it}] \; for \; j = 0{,}1 \quad (5)$$

My model specification adequately controls for unobserved variables that may be correlated with $D_{i,t}$. Covariates x_{it} control for state demographic statistics like average income, poverty rates, and racial makeup. Time fixed effects θ_t control for yearly economic trends that could influence state unemployment rates or the percent of a state's population at or below 138% FPL (the income needed to qualify for ACA Medicaid). State fixed effects control for time invariant characteristics like state debt, percent population uninsured, or political culture. It is particularly important to control for unmeasurable variables like political culture as partisanship may heavily influence a state's decision to expand policy.

Chapter 5

Results

My evidence suggests that in providing Medicaid to high poverty and high rent burdened counites, health insurance prevents personal medical expenses from becoming the serious financial shocks that lead to eviction. My findings support that ACA Medicaid expansion leads to a 10% decline in post treatment eviction rates.[18]

I have divided my findings into three sections and three tables. The first provides my baseline estimate, and various robustness checks, on γ, the estimator for the causal impact of ACA expansion on eviction. The second details the importance of fixed effects for accurately estimating γ. And the third provides a heterogeneity analysis that compares ACA expansion's causal impact across different subsamples.

Table 1: Robustness Check

Table 1 provides a robustness check that compares γ estimates across four different model specifications. γ is the coefficient for $ACA_{t,c}$ and estimates the treatment effect of ACA expansion.[19] γ is interpreted as the average, yearly difference between actual county level eviction rates (policy present) and counterfactual rates (policy absent) for counties in the post treatment period. To check the robustness of γ, I ran regressions across four different specifications, each of which includes a different set of covariates. Case 1 drops all regressors

[18] See Appendix D for full calculation

[19] $ACA_{t,c}$ is equivalent to the difference in difference interaction term $D_{i,t}$ described in Equation 3.1. It is a dummy variable where $ACA_{t,c} = 1$ when ACA Medicaid is expanded in year *t* for county *c*.

aside from the treatment effect dummy, $ACA_{t,c}$. Case 2 adds covariates related to county income and poverty levels and housing costs. Case 3 includes only regressors related to county racial demographics. Finally, Case 4 offers a base case specification that includes all regressors from the previous three cases.

TABLE 1 – ROBUSTNESS CHECK

	Beta Estimates by Regression Case			
Independent Variables	Case 1: 'None'	Case 2: 'Income, Housing'	Case 3: 'Race'	Case 4: 'Base Case'
$ACA_{t,c}$ [Coeff. (γ)]	-0.14804*** (0.021974)	-0.1555*** (0.022014)	-0.15457*** (0.021998)	-0.15954*** (0.022039)
Poverty Rate	X	-0.00629** (0.002)	X	-0.00535* (0.002)
Rent Burden	X	0.0009 (0.002)	X	0.00021 (0.002)
Median Gross Rent	X	-0.00081*** (0.0001)	X	-0.00073*** (0.0001)
Pct. Renter Occupied Housing	X	-0.00571* (0.002)	X	-0.00502* (0.002)
Pct. White	X	X	0.01618** (0.005)	0.01087 (0.006)
Pct. African American	X	X	0.02055** (0.007)	0.01518* (0.007)
Pct. Hispanic	X	X	0.00176 (0.006)	0.00018 (0.007)
Constant	1.58832*** (0.018)	2.35285*** (0.144)	0.13474 (0.518)	1.2745* (0.593)
N Observations	41,339	41,299	41,339	41,299

<u>For all cases:</u>
Dependent Variable: eviction rate per county per year
Regressed on full data set N = 41,299
Standard Error Below Coefficient
P-Value coding: * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Figure 3. Robustness Check

Table 1 shows γ to be a robust estimator, as my model consistently estimates its value across different specifications. Despite adding and dropping regressors related to racial demographics, income, and housing values, the magnitude of my γ estimates remained nearly equal. Across all cases, γ estimates were statistically significant at the 0.001 level and maintained a negative sign. This suggests that my model does not depend on specific independent variables to estimate γ. This robustness exercise supports γ as a valid estimate for the treatment effect of ACA Medicaid policy on eviction rates.

Table 2: Comparing Models with and Without Fixed Effects

Table 2 compares regression output for models with and without two-way fixed effects. This exercise establishes that fixed effects are necessary to estimating γ values representative of the true population parameter (the causal effect of ACA policy on eviction rates). Two-way fixed effects control for unobservable unit-specific and time-specific variables. In the context of my research, this means controlling for counties' propensity towards eviction and the macroeconomic trends/shocks that influence yearly changes in eviction rates. Without fixed effects, γ estimates are likely biased as they are not estimated through difference in difference. Instead of estimating the causal impact of policy, γ may instead express cross state differences that are correlated with expansion. Expansion counties on average have lower poverty rates, larger incomes, and lower eviction rates than non-expansion counties (See Appendix B). Without fixed effects, γ estimates would have larger negative magnitudes, reflecting expansion counties' disinclination towards eviction as opposed to representing ACA policy's true impact on eviction rates.

TABLE 2 – COMPARING MODELS WITH AND WITHOUT TWO-WAY FIXED EFFECTS

Independent Variables	Case 1: 'None' (FEs)	Case 1: 'None' (No FEs)	Case 2: 'Income, Housing' (FEs)	Case 2: 'Income, Housing' (No FEs)	Case 3: 'Race' (FEs)	Case 3: 'Race' (No FEs)	Case 4: 'Base Case' (FEs)	Case 4: 'Base Case' (NO FES)
	Beta Estimates by Regression Case							
$ACA_{t,c}$ [Coeff. (γ)]	-0.14804*** (0.021974)	-0.22696*** (0.018)	-0.1555*** (0.022014)	-0.24885*** (0.019)	-0.15457*** (0.021998)	-0.22910 (0.018)	-0.15954*** (0.022039)	-0.24831*** (0.019)
Poverty Rate	X	X	-0.00629** (0.002)	-0.01188*** (0.002)	X	X	-0.00535* (0.002)	-0.01516*** (0.002)
Rent Burden	X	X	0.0009 (0.002)	0.01132*** (0.002)	X	X	0.00021 (0.002)	0.00951*** (0.002)
Median Gross Rent	X	X	-0.00081*** (0.0001)	0.00045*** (0.000)	X	X	-0.00073*** (0.0001)	-0.00041*** (0.000)
Pct. Renter Occupied Housing	X	X	-0.00571* (0.002)	0.00721*** (0.002)	X	X	- 0.00502* (0.002)	0.00600** (0.002)
Pct. White	X	X	X	X	0.01618** (0.005)	-0.00477 (0.004)	0.01087 (0.006)	0.00281 (0.004)
Pct. African American	X	X	X	X	0.02055** (0.007)	-0.02893*** (0.004)	0.01518* (0.007)	0.03920*** (0.004)
Pct. Hispanic	X	X	X	X	0.00176 (0.006)	-0.00860 (0.004)	0.00018 (0.007)	-0.00551 (0.004)
Constant	1.58832*** (0.018)	1.79159*** (0.036)	2.35285*** (0.144)	1.35871*** (0.086)	0.13474 (0.518)	1.98274*** (0.362)	1.27450* (0.593)	0.87141* (0.497)

For all cases:
Dependent Variable: eviction rate per county per year
Regressed on full data set N = 41,299
Standard Error Below Coefficient
P-Value coding: * p<0.05, ** p<0.01, *** p<0.001

Figure 4. Comparing Models with and Without Fixed Effects

In Table 2, non-fixed effect estimates for γ have a magnitude that is on average 1.54 times larger than the γ estimates produced in their equivalent fixed effects cases. These γ estimates suggest that ACA Medicaid expansion had a greater reductive impact on eviction rates than previously estimated. This agrees with my previous predictions that expansion counties' lesser propensity towards eviction would lead to greater magnitude γ estimates. Additionally, without time fixed effects, γ estimates are likely further biased by national eviction rate trends, which between 2014 and 2016 showed an annual decline in average rates (See Appendix A). This downward eviction trend may be influenced by broader macro-level trends like falling unemployment, which maintained a post-recession decline between 2014 and 2016.[20] Therefore, the models that include fixed effects are better able to control for year-to-year macroeconomic trends and estimate only the casual impact of ACA policy on eviction rates.

Table 3: Heterogeneity Analysis

Table 3 presents heterogeneity analysis to show how ACA Medicaid expansion impacts eviction rates for different subsamples. This analysis helps answer the following questions: Which counties are most vulnerable to eviction? In which counties does ACA expansion have the greatest reductive effect on eviction rates? And do the demographics of these counties match the demographics of those populations targeted by ACA Medicaid expansion?

Table 3 divides counties by poverty rate, rent burden, and population. I use poverty rates to indicate which counties are more likely to have residents eligible for ACA Medicaid. Under ACA expansion, individuals are eligible if they have income at or below 138% of the federal poverty line. Rent burden calculates median monthly rent as a percentage of median household income. I use this statistic to measure a county's affordable housing stock, and I deem counties with rent burden > 30 to have less affordable housing.[21] Additionally, counties are classified as Small, Medium, or Large depending on population size. All statistics in Table 3, aside from the column titled 'Coeff. (γ)', are derived from a subset of observations that include expansion

[20] Taken from the BLS report: Labor Force Statistics from the Current Population Survey Overview, 2020

[21]. The department of Housing and Urban Development defines an 'affordable dwelling' as housing that accounts for 30% of household income. Using rent burden as a proxy for this measurement, counties with RB > 30% have a lower availability of affordable housing units.

counties for years 2014-2016. I focus my post-regression analysis on this smaller set of data because the interpretation of γ pertains to the post treatment time period.

TABLE 3 – HETEROGENEITY ANALYSIS: EXPANSION COUNTIES, POST-TREATMENT

Sub Sample	% of sample	Coeff. (γ)	Eviction Rate	Counterfactual Eviction Rate	% Change in Eviction Rates	Total Evictions	Evictions Saved
All Counties	100%	-0.15954*** (0.022)	1.435666	1.595202	-10.00%	1,001,441	111,283
County Rent Burden <= 30%	61.43%	-0.06431* (0.025)	1.338689	1.403003	-4.58%	305,879	14,695
County Rent Burden > 30%	38.57%	-0.30855*** (0.045)	1.600477	1.909031	-16.16%	695,562	134,097
Small Population [0,25000)	43.70%	0.01057 (0.027)	0.804970	0.815540	-1.30%	14,678	193
Medium Population [25000, 100000)	32.94%	-0.31982*** (0.042)	1.782766	2.102582	-15.21%	89,229	16,007
Large Population [100000, ∞)	23.36%	-0.22643*** (0.062)	2.217795	2.444224	-9.26%	897,534	91,635
County Poverty Rate <= 10.485%	50%	-0.08575** (0.03)	1.235633	1.321378	-6.50%	341779	23,717
County Poverty Rate >= 10.485%	50%	-0.21533** (0.032)	1.643688	1.859022	-11.58%	659662	86,420
County Poverty Rate > 15.5%	16.97%	-0.09963 (0.056)	1.330522	1.430151	-7.00%	145,823	10,919
County Poverty Rate > 19%	7.65%	-0.11024 (0.087)	1.02311	1.133348	-9.73%	103,975	11,203

Notes:
Standard Error Below Coefficient
P-Value coding: * p<0.05, ** p<0.01, *** p<0.001

Dependent variable: eviction rate per county per year.
Estimates for (γ) come from regressions that include two-way fixed effects, interaction term 'ACA_tc'.

Regressions include following covariates:
poverty rate, median household income, median gross rent, rent burden, median property value, pct. renter occupied housing, pct. White (Non-Hispanic or Latino), pct. African American, pct. Hispanic

Data Source: Eviction Lab at Princeton University, which includes ~
2000 Census, 2010 Census, and 5-year estimates from the 2009, 2012, and 2015 American Community Surveys.

Figure 5. Heterogeneity Analysis

The key finding from this analysis is that evictions occur at a higher rate, and that ACA Medicaid policy has a larger reductive effect on evictions, within counties with high poverty rates. Counties with poverty rates above the median rate of 10.485% recorded roughly 2x more evictions than expansion counties with poverty rates below the median. I expected this result as poverty indicates low-income and suggests greater financial instability. Within these same counties, I estimate that ACA Medicaid expansion reduced eviction rates by 11.58%. Comparatively, for counties with poverty rates below the median value, Medicaid expansion led to an estimated 6.5% decrease in eviction rates.

Seeing greater reductions to eviction rates in high poverty counties suggests that under new ACA guidelines, Medicaid is providing broader financial protection. Prior to ACA expansion, Medicaid was offered to disabled adults and eligible families that met income standards determined by the Aid to Families with Dependent Children (AFDC) program. Now in expansion states, Medicaid eligibility depends only on an individual's income level. This means high poverty counties will have more eligible enrollees. Following my hypothesis, as eligible individuals enroll in Medicaid, eviction rates fall as the financial externalities of insurance prevent medical bills from becoming the income shocks that lead to eviction.

Chapter 6

Conclusion

Implications

Using a back of the envelope calculation, I extrapolate the number of evictions prevented by ACA Medicaid expansion. These figures represent unintended benefits of ACA Medicaid expansion and may be of interest to policy makers. Utilizing '% change in eviction rate' figures from Table 3, I estimate prevented evictions with:

$$\text{'Prevented Evictions'} = \left[\frac{\text{Total Evictions}}{1-|\text{pct change evictions}|}\right] - \text{Total Evictions}$$ [22]

Between 2014 and 2016, I estimate that ACA Medicaid expansion prevented 111,283 evictions from occurring in expansion states. Had the remaining 24 states opted to expand ACA Medicaid coverage in 2014, policy would have prevented an additional 172,077 evictions between that year and 2016. Together, had all states expanded ACA Medicaid in 2014, I estimate that policy would have prevented a total of 283,360 evictions between 2014 and 2016. Conversely, had no states expanded policy, the absence of ACA Medicaid would have led to an excess of 125,196 evictions in what would have been expansion counties.

These results come from a dataset that only records formal, court ordered evictions. Desmond and Shollenberger (2015) estimates that formal evictions account for only half of all national evictions. Accounting for these additional cases would then double the number of evictions in the dataset. Assuming that ACA Medicaid expansion prevents informal evictions

[22] Here, the left side fraction calculates the counterfactual number of evictions for a subsample had there been no policy intervention. 'Pct. change eviction' is calculated using the same equation described above in the Robustness section.

through the same mechanisms that it prevents formal evictions, I estimate that policy would then prevent 566,720 evictions.

Existing literature shows that evictions can lead to housing instability, negative mental health outcomes, and reduced job security. Preventing eviction may then alleviate these consequences. Greiner, Pattanayak, and Hennessy (2013) notes that federal housing agencies can deny housing assistance to individuals who have been evicted in the last five years. In the private housing market, landlords use tenant screening reports and often turn away those who have eviction records (Kleysteuber, 2006). This can influence a tenant's next housing options. Desmond and Shollenberger (2015) finds that renters who experience a forced move later live in neighborhoods with significantly higher poverty and crime rates than renters who move by choice.[23] Eviction has also been found to affect mental health and job security. Desmond and Kimbro (2015) finds that evicted mothers, "compared to matched mother who were not evicted in the previous year, were more likely to suffer from depression". Desmond and Gershenson (2015) finds that workers who have been evicted are 11-15% more likely to be laid off than matched workers who have not. This job displacement can lead to lower paying jobs and persistent earnings losses.[24] Through the mechanism I have proposed in this paper, ACA expansion provides the financial protection necessary to prevent evictions and their accompanying consequences.

[23] Poverty rates are 5.4 percentage points higher and crime rate are nearly 1.8 percentage points higher (Desmond Shollenberger)

[24] Farber (2005) and Ruhm (1991) find that "Displaced workers who find new jobs on average earn roughly 17 percent less than they would have had they been continuously employed" (as cited in Desmond and Gershenson 2015). Couch and Placzek (2010) and Gangl (2006) conclude that "earnings losses of laid off workers are stubbornly resilient, persisting for as long as 20 years post displacement" (as cited in Desmond Gershenson 2015).

Further Research:

This research can benefit from additional analysis on stakeholder outcomes. Estimating the cost of eviction would help convert my prevented eviction figure into dollar savings for landlords and local governments. This figure could be particularly interesting for policy makers and local government budget offices. However, is it very difficult to find a consistent estimate for eviction cost. For landlords, eviction costs come from legal fees, court fees, lost rent, and property turnover costs. I found estimates that ranged between $3,500-$7,300 dollars per eviction. However, the statistics came from private tenant screening companies that often use these numbers to promote their software products to landlords. Finding a more reputable estimate is necessary before estimating the cost of eviction to landlords. As for local governments, (Elliott, Martinchek & Kalish, 2019) estimates the cost of eviction by proxying a city's annual spending per homeless family. The report examines 10 cities; however, using this proxy, eviction costs ranged from $464 to $20,162. Because of this large range, more localized cost estimates are needed before estimating the dollar savings of each prevented eviction.

Additionally, a difference in difference matching estimator would improve the accuracy of my γ estimate by using more suitable comparison groups to determine the causal effect of ACA policy. My current model estimates γ by comparing the change in eviction rates for all expansion counties against the change in eviction rates for all non-expansion counties. A matching estimator would instead compare demographically similar counties whose only observable difference lies in expansionary status. For example, comparing eviction rate changes in a suburb of Columbus, Ohio (an expansion state) to eviction rate changes in a suburb of Indianapolis, Indiana (a non-expansion state) produces a more accurate γ estimate than comparing averages across all expansion and non-expansion sates.

Appendix A

Annual Statistics for Formal Eviction Activity

Annual Statistics for Formal Eviction Activity			
year	evictions	eviction-filing	eviction-rate
2000	518873	1159168	2.68
2001	754652	1750452	2.75
2002	864918	2085491	2.88
2003	910361	2134014	3
2004	940817	2177018	3.06
2005	969303	2306580	3.03
2006	1019600	2441067	3.13
2007	958605	2002531	3.07
2008	996233	2079865	3.11
2009	952699	2108719	2.91
2010	993531	2374084	2.95
2011	987999	2452080	2.91
2012	983666	2420135	2.84
2013	930693	2378464	2.63
2014	908977	2394318	2.5
2015	870325	2288732	2.38
2016	898479	2350042	2.34

Appendix B

Demographic Characteristics of Expansion vs Non-Expansion States

DEMOGRAPHIC CHARACTERISTICS OF TREATMENT AND CONTROL STATES (AVERAGES)

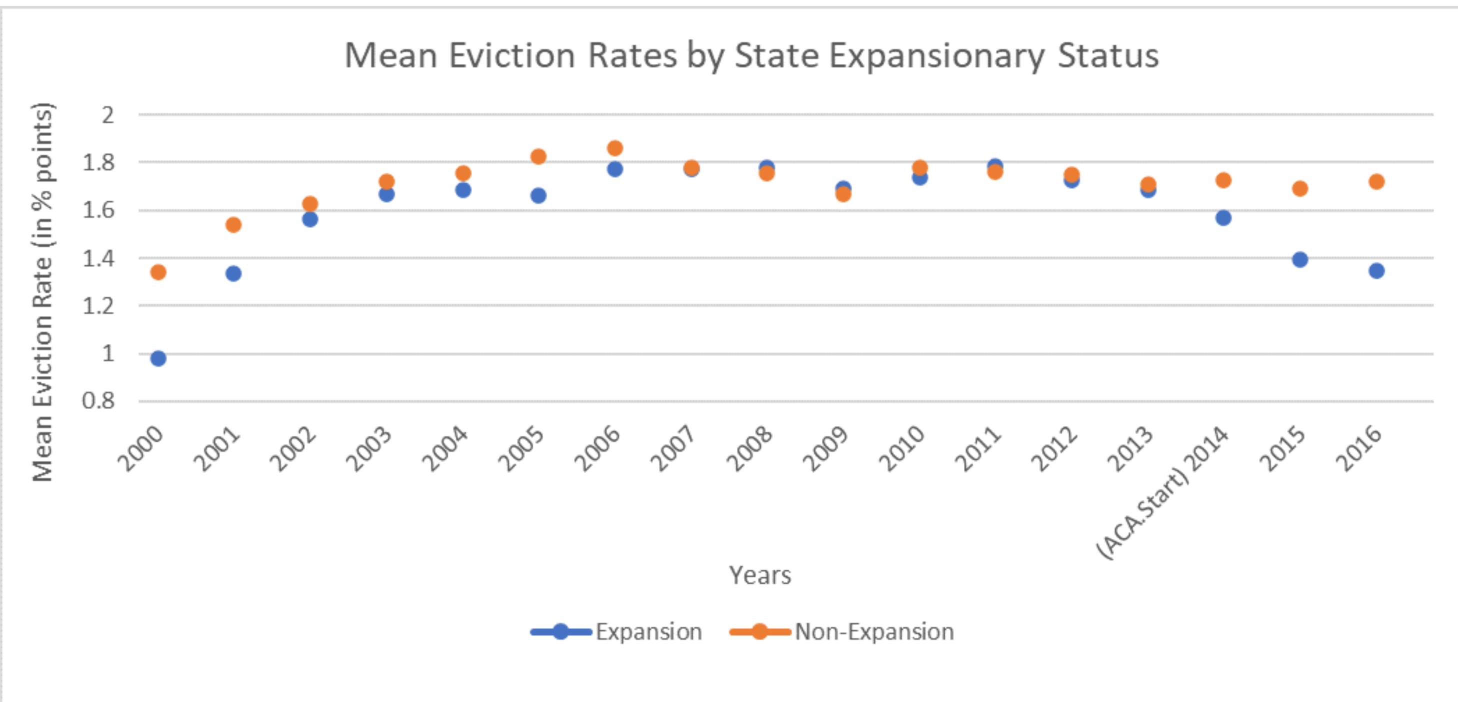
Demographic	Expan (A)	Non-Expan (B)	Difference (C) = (A) – (B)
Poverty rate	11.458	13.176	-1.718
	(5.621)	(6.274)	
Median HH Income	$44,627	$41,042	$3,585
	(23,095)	(21,784)	
Rent burden	27.345	26.396	0.949
	(4.578)	(4.854)	
Renter occupied	27.19	27.397	-0.207
	(8.262)	(7.855)	
Population	137,000	70,931.15	66068.85
	(439,000)	(188,000)	
Percent white	84.086	76.056	8.03
	(17.078)	(20.387)	

Notes: Columns (A) and (B) present mean values across time period 2000-2016. Column (C) shows the difference in means. Standard deviations are in parentheses.
Poverty rate: '% of the population with income in the past 12 months below the poverty'
Rent burden: 'Median gross rent as a percentage of household income'
Renter occupied: '% of occupied housing units that are renter-occupied'
Data Source: 2000 Census, 2010 Census, and 5-year estimates from the 2009, 2012, and 2015 American Community Surveys.
Additional Notes: all data were recorded at the county level. All variable definitions come from 'Eviction Lab Dictionary'

Appendix C

Visual Validation of Parallel Trends Assumption

By plotting yearly eviction rates by group, over time, it is possible to observe parallel trends between expansion and non-expansion counties. When, "year-to-year volatility is relatively low, it is easy to spot deviations from the common trends assumption in a long time series" (Wing, Simon, Bello-Gomez, 2018). Graphically, we see that eviction rates from my data follow a similar annual trend for both groups in the pre-treatment period. Additionally, the line plot is absent of any noticeable inter-group volatility. Therefore, we use this graph to validate the parallel trends assumption.



Appendix D

Equation Used to Calculate % Change in Evictions

I derived the '% change in eviction' statistic by calculating a percent change between the actual mean eviction rate (policy present) and the counterfactual mean eviction rate (policy absent) in the post treatment period for expansionary counties.

[$(Y(1)_{i=1,t=2} – Y(0)_{i=1,t=2}) /(Y(0)_{i=1,t=2})$]:

$(Y(1)_{i=1,t=2})$ is the actual mean eviction rate for expansion counties, post treatment

$(Y(0)_{i=1,t=2})$ is the counterfactual mean eviction rate for expansion counties, post treatment

I calculate the counterfactual: $(Y(0)_{i=1,t=2}) = (Y(1)_{i=1,t=2}) + |\gamma|$

BIBLIOGRAPHY

Allen, Heidi & Swanson, Ashley & Wang, Jialan & Gross, Tal. (2017). “Early Medicaid Expansion Associated With Reduced Payday Borrowing In California.” *Health Affairs*. 36, 1769-1776. 10.1377/hlthaff.2017.0369.

Angrist, J. D., & Pischke Jörn-Steffen. (2013). *Mostly Harmless Econometrics: An Empiricists Companion*. United States: Content Technologies Inc.

Besley, T., & Case, A. (2000). Unnatural Experiments? Estimating the Incidence of Endogenous Policies. *The Economic Journal*, *110*(467), 672–694. doi: 10.1111/1468-0297.00578

Brevoort, K., D. Grodzicki, and M. B. Hackmann (2017). Medicaid and financial health. NBER Working Paper 24002.

Caswell, K. and T.Waidmann (2017). The affordable care act medicaid expansions and personal finance. *Medical Care Research and Review*.

Dobkin, C., Finkelstein, A., Kluender, R., & Notowidigdo, M. J. (2018). The Economic Consequences of Hospital Admissions. *The American Economic Review*, *102*(2), 308–352. doi:10.1257/aer.20161038

Downs, Anthony. 2008. “Introduction: Why Rental Housing is the Neglected Child of American Shelter.” Pp. 1–13 in Revisiting Rental Housing: Policies, Programs, and Priorities, edited by N. Retsinas and E. Belsky. Washington, DC: Brookings Institutions Press.

Desmond, Matthew. 2015. "Unaffordable America: Poverty, Housing, and Eviction." Fast Focus, Institute for Research on Poverty 22.

Desmond, Matthew, Carl Gershenson, and Barbara Kiviat. 2015. "Forced Mobility and

Residential Instability among Urban Renters." *Social Service Review*.

Desmond, M., & Kimbro, R. T. (2015). Eviction's fallout: Housing, hardship, and health. *Social Forces*. doi:10.1093/sf/sov044

Desmond, Matthew and Tracey Shollenberger. 2015. "Forced Displacement from Rental Housing: Prevalence and Neighborhood Consequences." *Demography* 52:1751–72.

Desmond, M. (2016). *Evicted*. Crown/Archetype.

Elliott, D., Martinchek, K., & Kalish, E. (2019, November 6). The Cost of Eviction and Unpaid Bills of Financially Insecure Families for City Budgets.

Federal Poverty Level (FPL). (n.d.). Retrieved March 21, 2020, from https://www.healthcare.gov/glossary/federal-poverty-level-fpl/

Finkelstein, A., S. Taubman, B. Wright, M. Bernstein, J. Gruber, J. Newhouse, H. Allen, and K. Baicker (2012). The Oregon Health Insurance Experiment: Evidence from the first year. *Quarterly Journal of Economics* 127(3), 1057–1106.

Frees, E.W. (2010). Fixed Effects Models. In *Longitudinal and Panel Data Analysis and Applications in the Social Sciences.* Oxford University Press.

Gallagher, Emily A., Radhakrishnan Gopalan, and Michal Grinstein-Weiss. "The Effect of Health Insurance on Home Payment Delinquency: Evidence from ACA Marketplace Subsidies." *Journal of Public Economics* 172 (April 2019): 67–83.

Greiner, D. James, Cassandra Wolos Pattanayak, and Jonathan Hennessy. 2013. "The Limits of Unbundled Legal Assistance: A Randomized Study in a Massachusetts District Court and Prospects for the Future." *Harvard Law Review* 126:901-89.

Hamel, Liz, Mira Norton, Karen Pollitz, Larry Levitt, Gary Claxton, and Mollyann Brodie. 2016. The burden of medical debt: Results from the Kaiser Family

Foundation." New York Times medical bills survey.

Hu, L., Kaestner, R., Mazumder, B., Miller, S., & Wong, A. (2018). The Effect of the Affordable Care Act Medicaid Expansions on Financial Wellbeing. *Journal of Public Economics*, *163*, 99–112. doi:10.1016/j.jpubeco.2018.04.009

Kleysteuber, Rudy. 2006. "Tenant Screening Thirty Years Later: A Statutory Proposal to Protect Public Records." *Yale Law Journal* 116:1344-88.

Labor Force Statistics from the Current Population Survey Overview. (2020, March 24).

La Jeunesse, Elizabeth, et al. "Documenting the Long-Run Decline in Low-Cost Rental Units in the US by State." Cambridge, MA: *Joint Center for Housing Studies*, September 2019.

Matthew Desmond, Ashley Gromis, Lavar Edmonds, James Hendrickson, Katie Krywokulski, Lillian Leung, and Adam Porton. Eviction Lab Methodology Report: Version 1.0. Princeton: Princeton University, 2018, www.evictionlab.org/methods.

Matthew Desmond, Ashley Gromis, Lavar Edmonds, James Hendrickson, Katie Krywokulski, Lillian Leung, and Adam Porton. Eviction Lab National Database: Version 1.0. Princeton: Princeton University, 2018, www.evictionlab.org.

Miller, Sarah, Luojia Hu, Robert Kaestner, Bhashkar Mazumder, and Ashley Wong. "The ACA Medicaid Expansion in Michigan and Financial Health." Cambridge, MA: National Bureau of Economic Research, September 2018. https://doi.org/10.3386/w25053.

Miller, S. and L. Wherry (2017). Health and access to care during the first 2 years of the aca medicaid expansions. *New England Journal of Medicine* 376, 947–956.

"Non-Disabled Adults." *MACPAC*, www.macpac.gov/subtopic/nondisabled-adults/.

Oishi, Shigehiro. 2010. "The Psychology of Residential Mobility: Implications for the Self, Social Relationships, and Weil-Being." *Perspectives on Psychological Science* 5(1):5-21.

Rice, Douglas and Barbara Sar. 2009. Decade of Neglect has Weakened Federal Low-Income Programs: New Resources Required to Meet Growing Needs. Washington, DC: Center on Budget and Policy Priorities.

Temple, Judy A., and Arthur J. Reynolds. 1999. "School Mobility and Achievement: Longitudinal Findings from an Urban Cohort." *Journal of School Psychology* 37(4):355-77.

Williams, R. (2018, March 20). Panel Data 4: Fixed Effects vs Random Effects Models.

Retrieved from https://www3.nd.edu/~rwilliam/stats3/Panel04-FixedVsRandom.pdf

Wing, C., Simon, K., & Bello-Gomez, R. A. (2018). Designing Difference in Difference Studies: Best Practices for Public Health policy Research. *Annual Review of Public Health*, 39(1), 453-469. Doi: 1 0.1146/annurev-publhealth-040617-013507

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RELEVANT EXPERIENCE

Penn State Department of Economics | University Park, PA May 2019-Present
Undergraduate Summer Research Assistant for Dr. Paul Grieco

- Designed an Excel data cleaning method to organize 20 years of raw data for an emerging dataset on the US auto industry
- Utilize MATLAB data structures and histograms to illustrate research findings for academic publications and presentations
- Assist professor in preparation for conferences in China and Barcelona by editing and reviewing lecture materials

Research Experience for Undergraduates (REU) Program

- Paid research opportunity to continue work with Dr. Grieco for the Fall 2019 semester

INTERNATIONAL EXPERIENCE

IES Abroad, Madrid, Spain Jan.-May 2019
Spanish Language and Area Studies

Escuela de Organización Industrial (EOI) | Madrid, Spain Jan.-May 2019
Assistant to the Head of Resident Life

- Worked for four months in a Spanish speaking office
- Analyzed and organized housing data on 215 students to help management team determine housing demand for 2020
- Translated EOI's housing application, code of conduct, and data release form to inform and attract English-speaking students

COMMUNITY LEADERSHIP & INVOLVEMENT

Penn State Alternative Breaks | University Park, PA; Selma, Alabama; Beaumont, Texas Oct. 2017-Jan. 2019
Site Leader

- Planned and executed education/service-learning trips for Penn State students that focused on race relations and disaster relief
- Led pre-trip trainings to educate participants and prepare them to enter host-communities with knowledge and respect
- Collaborated with co-site leader and project partners to create a week-long itinerary that engaged participants in direct community service, seminars, speaking events, museum visits, and reflection activities related to the civil rights movement
- Coordinated Hurricane Harvey recovery work by assessing homeowner needs and delegating tasks to team members

American Conservation Experience | St. George, Utah May 2017-Aug. 2017

AmeriCorps Volunteer/ Corps Member

- Lived in Utah for 12 weeks, completing 450 hours of trail work on National Park and National Forest land
- Built and maintained over 20 miles of trails, increasing community and tourist access to natural and cultural sites
- Worked and lived within a crew of eight people while on project in remote wilderness areas

Penn State Center Engaging Philadelphia | Philadelphia, PA June 2018-Aug. 2018

Community Engagement Intern

- Learned about urban agriculture's capacity to create safer, stronger, and more economically resilient communities
- Farmed for over 250 hours on a small scale organic farm in Philadelphia, working closely with field managers to produce vegetables for a weekly CSA program serving 150 local families
- Mentored area high school students through the Philadelphia Youth Network by providing college preparation advice

Penn State Club Cross Country | Competing Member Aug. 2016-Present

- Top 10 finisher at the 2019 NIRCA club national championship; 2020 Boston Marathon qualifier