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This dissertation explores the prevalence and prevention of rental housing evictions. I begin by providing a systematic review of the eviction literature. I find from my review of the literature over the past 20 years that attention to eviction has greatly increased. Next, I develop a theoretical model for the county-level eviction rate. By incorporating both landlord and tenant situations into the model, I find that the eviction rate can increase or decrease depending on eviction costs paid by landlords, hardship experienced by renters, or support provided to renters. Finally, I use data from the Eviction Lab, the first national database on eviction, to study three unanswered questions: (1) what is the extent of the US eviction crisis? (2) what is associated with the variation in eviction rates across US counties? And (3) can unemployment insurance (UI) benefits serve as an eviction prevention program? First, I find that the US eviction crisis is characterized primarily by consistently high rates of eviction at the national, state, and local levels. Second, I find that both demographic and economic factors are strongly related to the variation in eviction rates across US counties. Third, I find that UI benefits can serve as an eviction prevention program, but in doing so they induce landlords to file on their tenants more often, which results in worse outcomes for some tenants. Overall, this dissertation expands the literature on the prevalence and prevention of rental housing evictions, which ultimately aids policymakers and private organizations trying to reduce or prevent evictions.

ON THE PREVALENCE AND PREVENTION OF RENTAL HOUSING EVICTIONS

by

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Approved by

____
Committee Chair

To my parents, who just wanted me to finish my dissertation.

For my sister younger and our family dog, who just wanted me to hang out with them.

APPROVAL PAGE

This dissertation written by KELSI GABRIELLE HOBBS has been approved by the following committee of the Faculty of The Graduate School at The University of North Carolina at Greensboro.

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CHAPTER I

INTRODUCTION

According to estimates from the Eviction Lab, the first national database on eviction, US landlords file over 2 million evictions per year (Desmond et al., 2018a). Nearly 40 percent of these eviction filings result in an eviction judgment, where an individual or a family is removed from their home. The current levels of eviction filings track levels of foreclosure filings during the peak of the foreclosure crisis. According to data from ATTOM data solutions, over 2.8 million US properties had foreclosure filings in 2010 (ATTOM, 2019). This similarity has led journalists and scholars to suggest that the US is in the midst of an *eviction crisis* (Brennan, 2018; Capps, 2018; Goldberg, 2018; Gergen & Mayer, 2018; Sills et al., 2018).

Previous research ties eviction to numerous negative consequences. For families, eviction can lead to homelessness, (Crane & Warner, 2000; Collinson & Reed, 2018), residential instability (Desmond & Shollenberger, 2015; Desmond et al., 2015; Collinson & Reed, 2018), and economic hardship (Humphries, et al., 2018, Kahlmeter et al., 2018). For adults, eviction is tied to job loss (Desmond & Gershenson, 2016a), as well as physical and mental health issues (Desmond & Kimbro, 2015; Vasquez-Vera, 2017; Collinson & Reed, 2018; Rojas & Stenberg, 2018). Further, the consequences of eviction are not limited to those who experience it directly. Studies from ten different US cities show that the costs of eviction, unpaid property taxes, and unpaid utility bills to the community can range from tens to hundreds of millions of dollars (Elliot and Martinchek, 2019). Eviction can place direct and indirect fiscal costs on governments, taxpayers, and social-welfare groups as they pay for sidewalk cleanup, enforcement of evictions, homelessness, and increases in individuals requiring aid (Lindsey, 2010). During the ongoing pandemic, eviction could further the spread of the coronavirus, which is a public health concern (CDC, 2020a).

Despite high levels of eviction and numerous studies, the US eviction crisis is still not well understood. In their 2003 article, Hartman and Robinson referred to eviction as the "hidden housing problem". The authors called for a national database on eviction to be built and for more scholars to study eviction. Although more scholars have studied eviction since then, a national database on eviction, the Eviction Lab, was only released in 2018. As a result, the prior literature is limited by data.

Previous research primarily focuses on the causes and consequences of eviction, but most of the literature draws conclusions using data from one city or county, most of which are urban areas. Although these studies provide insight, it is difficult to know if the results are generalizable. Further, the literature has not focused on developing a theoretical framework within which to situate the study of eviction. Finally, the literature does little to suggest how we might prevent rental housing evictions. The release of the Eviction Lab provides an opportunity to study eviction more thoroughly because it provides estimates of eviction filings and eviction judgements at various geographic levels for the entire US.

This dissertation explores the prevalence and prevention of rental housing evictions in several ways. First, it provides a systematic review of the eviction literature. Second, it develops a theoretical model for the county-level eviction rate. Third, it uses data from the Eviction Lab to study three unanswered questions: (1) what is the extent of the US eviction crisis? (2) what drives the variation in eviction rates across US counties? And (3) can unemployment insurance (UI) benefits serve as an eviction prevention program?

This dissertation proceeds as follows. In Chapter II, I begin by providing a summary of the key aspects of landlord-tenant law and the eviction process. I then provide a systematic review of the eviction literature. I find from my review of the literature over the past 20 years that attention to eviction has greatly increased. Further, the distribution of the topics of focus of this research is skewed towards the causes and consequences of eviction.

In Chapter III, I develop a theoretical model of the county-level eviction rate. By incorporating both landlord and tenant situations into the model, I find that the eviction rate can depend on eviction costs paid by landlords, hardship experienced by renters, or support provided to renters. This model has implications for analyses in Chapter VII. In Chapter IV, I summarize the Eviction Lab database, describe my measures of eviction, and develop an adjustment measure for the quality of the Eviction Lab data.

In Chapter V, I use state- and county-level data from the Eviction Lab to determine the extent of the US eviction crisis. I find that the US eviction crisis is characterized by consistently high eviction filing and eviction judgment rates at the national, state, and local level. This result differs slightly from the foreclosure crisis, which was defined by both a spike in foreclosure rates during the Great Recession and a sustained period of historically high foreclosure rates after the Great Recession.

In Chapter VI, I determine what factors are associated with the variation in eviction filing rates and eviction judgment rates across US counties. Using data from nearly all US counties from 2005-2016, I find that both demographics and economics are associated the variation in eviction rates across US counties. However, the specific demographic and economic factors that are associated with higher eviction rates differ by outcome (eviction filing rates versus eviction judgment rates) and geography (all US counties versus urban US counties).

In Chapter VII, I explore the potential of UI benefits to serve as an eviction prevention program by mitigating the effect of unemployment on eviction. Exploiting variation in UI benefits across states and over time, I estimate the effect of state-level UI benefits on county-level eviction filing rates. I find that higher UI benefits can aid renters by mitigating the effect of unemployment on eviction. However, these higher benefits may also induce landlords to file on their tenants more often. Albeit counterintuitive, these results are consistent with recent literature on landlord-tenant interactions, particularly serial evictions. My results suggest that a clear understanding of the eviction process is necessary to creating effective eviction prevention policies.

In Chapter VIII, I conclude with a general discussion of the findings of the dissertation, as well as their implications. Overall, this dissertation explores the prevalence and prevention of rental housing evictions, which extends the current eviction literature. Extending the eviction literature is important, because only in understanding eviction can we hope to address the ongoing US eviction crisis. Effective solutions can only be created once there is a clear understanding of the problem. Overall, this dissertation provides new insight on the prevalence and prevention of rental housing evictions, which can ultimately aid policymakers and private organizations who aim to reduce or prevent evictions.

CHAPTER II

BACKGROUND

This chapter provides a background on eviction. I begin by briefly summarizing landlord-tenant law and the eviction process. I define terminology used throughout the rest of the dissertation. I then systematically review eviction literature. My systematic review establishes gaps in the literature, which I fill with the theoretical and empirical analyses of Chapters III, V, VI, and VII.

Landlord-Tenant Law

Landlord-tenant law oversees the relationship between landlords and tenants by directing the rights, rules, and responsibilities of both parties (AAOA, 2019). Each state maintains its own landlord-tenant statutes. These statutes concern prices, health and safety, rental unit possession, and antidiscrimination (Hatch, 2017). Although federal and local laws exist, most landlord-tenant law is enacted at the state-level (Hatch, 2017).

A number of states have drawn their landlord-tenant law from the Uniform Residential Landlord and Tenant Act from 1972 (Legal Information Institute, n.d.). However, recent research suggests there is significant variation in landlord-tenant policy across states. Hatch (2017) proposes that there are three distinct approaches: protectionist, probusiness, and contradictory. Protectionist states have mostly pro-renter laws. Probusiness states primarily protect landlords. Contradictory states have a variety of pro-renter and pro-landlord laws. For a comprehensive listing of existing landlord-tenant laws see Stewart and Portman (2018). For more on the typology of landlord-tenant policy approaches see Hatch (2017).

The Eviction Process

Eviction is an action taken by a landlord to remove a tenant from a rental property. In the United States, eviction is supposed to follow a legal process. However, previous research suggests that *informal evictions*, those where a landlord removes a tenant from a rental property without following the legal process, are prevalent (Desmond, 2012; Desmond & Shollenberger, 2015). As a result, I further define *formal evictions* as those that follow the legal process.

Due to data limitations, the prevalence of informal evictions across the United States is unknown. As a result, this dissertation focuses exclusively on formal evictions. The formal eviction process is guided by landlord-tenant laws and overseen by civil courts. Each state maintains its own laws and courts, which may differ from others. However, the process is generally the same and contains the following three steps: (1) file, (2) trial, and (3) judgement.

The formal eviction process begins when the landlord files for eviction. I define an *eviction filing* as the opening of an eviction case by the landlord. A landlord can file for eviction for many reasons. The three most common reasons are the tenant failing to pay rent, the tenant failing to maintain aspects of the lease, or the tenant remaining in the property after the lease ends (LexisNexis, 2017). After the eviction case is opened, the tenant is served a notice giving them a date to appear in court for a trial.

At trial, both landlords and tenants are given the opportunity to present evidence in their favor. Previous research suggests that most judgments are awarded in the landlord's favor (Sills et al., 2017; UNCC Urban Institute, 2018b). I define an *eviction judgment* as a decision in favor of the landlord, which results in possession of the property returning to the landlord and the tenant being removed from their home. However, not all eviction filings turn into eviction judgments. For example, the tenant may leave prior to the trial or the landlord and the tenant may come to an agreement (UNCC Urban Institute, 2017). In both cases, an eviction judgment is avoided.

Avoiding an eviction judgment is not always good news for a tenant. If the tenant remains in the home but fails to pay rent or maintain another aspect of the lease a second time, the landlord can file again. *Serial filings*, those that occur repeatedly for the same tenant in the same rental unit, are common. Nationally, over a third of all filings in 2014 were attributed to households who were filed against more than once (Leung et al., 2019). Among DC households with an eviction filing in 2018, nearly 60 percent had at least one other filing against them at some other point between 2014 and 2018 (McCabe and Rosen, 2020).

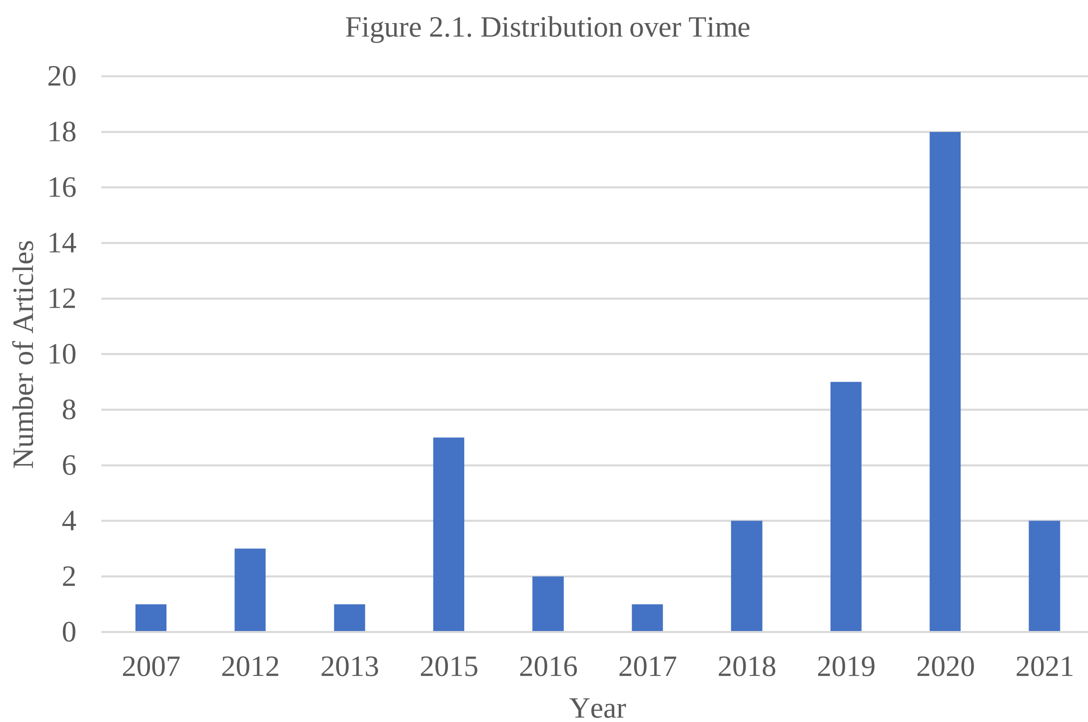
The analyses in later chapters will examine both eviction filings and eviction judgments. When I refer to evictions, I mean both filings and judgments.

The Eviction Literature

In their 2003 article, Hartman and Robinson refer to eviction as the "hidden housing problem". They provide a thorough review of the literature to that point in time. I review the peer-reviewed eviction literature since 2003 to establish the importance of eviction filings and eviction judgments, to determine what we know about eviction, and to describe the gaps in the literature, which my theoretical and empirical analyses in later chapters will address.

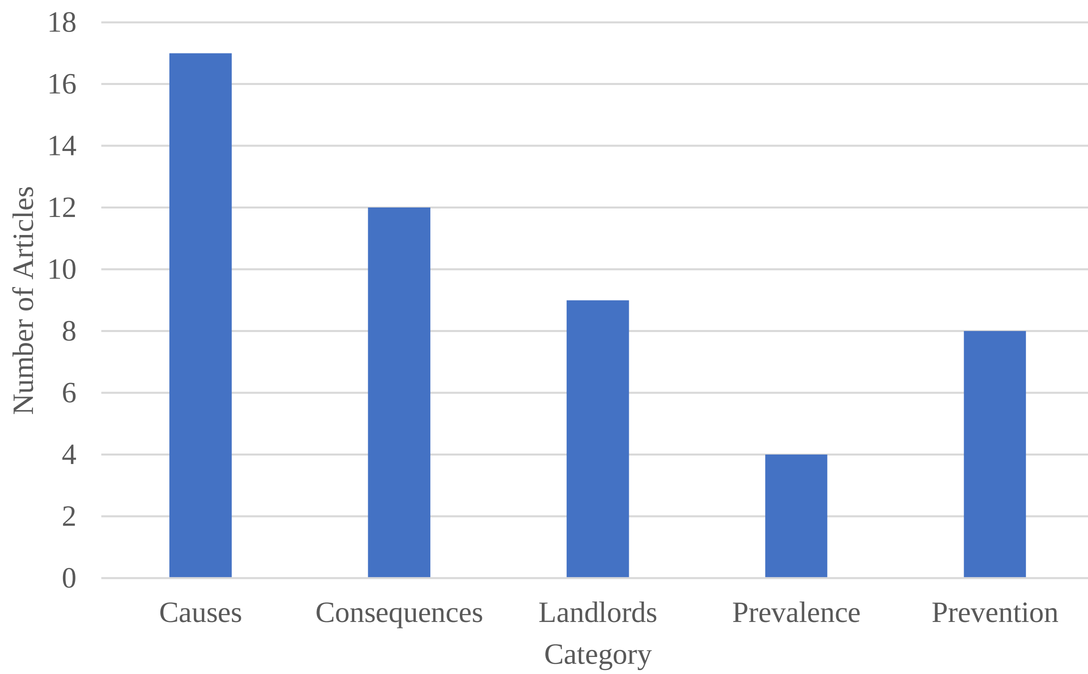
I collect relevant eviction literature using a systemic review method. To be sure I capture the most literature, I search "evict*" in the following databases: EconLit, RePEc, SocINDEX, JSTOR, and Scopus. I limit my search to titles and abstracts of journal articles in English. With this search method, I collect 172 articles from EconLit, 27 articles from RePEc, 378 in SocINDEX, 71 in JSTOR, and 164 in Scopus. Next, I read each title for relevance, which leaves me with 37 articles from EconLit, 1 article from RePEc, 56 articles from SocINDEX, 0 articles from JSTOR, and 40 articles from Scopus for a total of 134 articles. After removing duplicates, 103 articles remain. I then read each abstract for relevance, which leaves me with 81 articles. Next, I eliminate articles prior to 2003. Finally, after reading each article for relevance, I have 50 articles.

Figure 2.1 displays counts of peer-reviewed eviction articles over time. Between 2003 and 2012, only one article was published. After 2012, at least one article was published a year. In 2018, the Eviction Lab, the first national database on eviction was released. The release of new and better data may explain why in recent years, the number of articles has grown substantially.



In reading the articles, five broad themes emerge, which can be used to group the articles. These themes are prevalence, causes, consequences, prevention, and landlords. Figure 2.2 depicts the distribution of the theme of focus of the literature. Articles were categorized by the theme that was most present. The distribution is skewed towards the causes and consequences categories. I summarize the literature in each of these five themes in turn. Because articles could capture more than one theme, in the summaries that follow, some articles are discussed in more than one section. Additionally, I supplement my summary of the 50 articles from my systematic literature review with 6 local reports from North Carolina and Washington, DC that provide in depth studies of court cases.

Figure 2.2. Distribution by Category



Prevalence

Hartman and Robinson (2003) call for the establishment of a national database on evictions, because there is no systematic data collection at the national or local level (pp. 461). Without better data, it is impossible to know how many individuals were affected by eviction, nor who those individuals are, why they are being evicted, or what happens to them after (pp. 462). An understanding of these questions, the authors argue, would allow better development of housing policies and programs that would decrease the negative effects of this traumatic event (pp. 461).

Desmond (2012) studies the prevalence of eviction in Milwaukee, Wisconsin. Using eviction court records from 2003 to 2007, Desmond finds that landlords evict about 16,000 individuals from 6,000 units per year. These numbers equate to nearly 16 evictions per day, making eviction a frequent occurrence in the lives of Milwaukee renters. Desmond and Shollenberger (2015) studies the prevalence of involuntary mobility, which expands beyond formal evictions to include informal evictions, landlord foreclosure, or building condemnation. Using survey data from the Milwaukee Area Renters Survey (MARS), the authors find that 48 percent of all forced moves experienced by Milwaukee renters are informal evictions. Formal evictions only constitute 24 percent of forced moves. As a result, estimates using formal evictions likely undercount the prevalence of eviction by as much as half.

In 2018, Matthew Desmond and his team out of Princeton University released the Eviction Lab. Desmond et al. (2018a) is the first national database on rental housing evictions. The database suggests that over 2 million individuals experience a legal eviction filing each year, while over 900,000 are removed from their home each year. However, the database captures only formal evictions, not informal evictions. Lundberg and Donnelly (2018) estimate the proportion of children who are ever evicted during childhood (between birth and age 15). Using the Fragile Families and Child Wellbeing Study, they find that 14.8 percent of children born between 1998 and 2000 in large US cities are ever evicted between birth and age 15.

The development of a national database by Desmond et al. (2018a) is the first step towards better development of housing programs and policies to decrease the negative effects of eviction, as suggested by Harman and Robinson (2003). We now know that eviction is a common occurrence amongst renters, with the number of evictions much higher than previously thought.

Although we have estimates of the number of formal evictions in the US, we still do not know the true prevalence of informal evictions. The research suggests that it is nearly two times as much as formal evictions. The next question to be answered is: why are evictions so prevalent?

Causes

Hartman and Robinson (2003) find that eviction tends to affect lower-income individuals, as well as primarily women and minorities. More recent research comes to the same conclusions. A number of studies find that high eviction rates tend to be associated with race and ethnicity. Desmond (2012) finds that minorities are more affected by eviction. Using geographic information from Milwaukee County, Wisconsin eviction records, Desmond finds that the majority of those evicted are from black neighborhoods. Further, a comparison of means analysis shows that the average eviction rates in black and Hispanic neighborhoods are higher than those in white neighborhoods. These results hold even in high poverty and hyper segregated neighborhoods.

Lens et al. (2020) finds that evictions are most common in high black, high poverty areas in Los Angeles. These results suggest that race is the most important factor when it comes to higher eviction rates. Medina et al. (2020) finds that minority populations receive more eviction filings in Salt Lake City, UT. Nelson et al. (2021) finds that court-based fillings are more consistent spatially over time. The increased prevalence of court filings is most tied to the number of black residents. Finally, Hepburn et al. (2020) finds that eviction filing rates and eviction judgment rates are higher for black renters than for white renters. Furthermore, black and Latinx renters are more likely to face serial evictions.

Because minorities are disproportionately affected by evictions, studies try to determine if discrimination is at work. Greenberg et al. (2016) find that Hispanic renters are more likely to be evicted by non-Hispanic than Hispanic landlords. The authors use data from MARS. In their analysis, which uses discrete hazard models, they find that Hispanic renters are more likely to be evicted in majority white neighborhoods. Although the authors suggest discrimination against Hispanic tenants, they do not find evidence of discrimination against black tenants. However, they believe this lack of result could be due to racial residential segregation, a variable that has yet to be explored in the eviction literature.

Beyond race, a number of studies show that women, especially women with children are more likely to be evicted. Phinney et al. (2007) finds that 20 percent of low-income women have been evicted. Desmond (2012) finds evidence that women are significantly more affected by evictions than men, particularly black women. Using survey responses from the Milwaukee Eviction Court Study, an in-person survey of 251 tenants appearing in eviction court, Desmond finds that the majority of respondents lived with children. Over a third of respondents were women with children who lived with no other adults. Desmond (2015) cites his previous work when reinforcing the idea that women, as well as children, are more likely to be affected by eviction. Hepburn et al. (2020) finds that black and Latinx females have higher eviction rates than their male counterparts.

Desmond et al. (2013) suggests that children in and of themselves are a risk factor for eviction. The authors use Milwaukee County eviction cases and zero-inflated Poisson models to show that Census tracts with a higher percentage of children have higher eviction rates. In the same study, they use survey data from the Milwaukee Eviction Court Study, as well as logistic regression and propensity score analysis, to show that families with children are more likely to be evicted. Desmond and Gershenson (2016b) find similar results. Using the MARS data and discrete hazard models, the authors find that the presence of an additional child in a family increases that family's likelihood of eviction. Using data from Mercy Housing, an organization that offers affordable housing across 18 states, Brisson and Covert (2015) find that households in "family housing" are most at risk for receiving a lease violation for nonpayment of rent.

One of the most general reasons for eviction under the law is a tenant failing to pay rent (LexisNexis, 2017). A report by the Center for Housing and Community Studies (CHCS) at the University of North Carolina at Greensboro (UNCG) finds that 98.7 percent of all eviction cases in Guilford County, North Carolina listed nonpayment of rent on the eviction filing (Sills et al., 2017). A similar report by the Urban Institute at the University of North Carolina at Charlotte (UNCC) finds that 97 percent of all evictions in Charlotte-Mecklenburg County, North Carolina were due to nonpayment of rent (Urban Institute at UNCC, 2018b). A study on evictions in Washington, DC found that 93 percent of all eviction filings from 2014-2018 were for nonpayment of rent (McCabe and Rosen, 2020). Finnegan and Meagher (2019) suggest that income loss is significantly more likely to result in housing issues than utility issues.

Looking at national trends over time, Desmond (2015) and Desmond (2018) both imply that the rising cost of housing, flat-lined incomes, and as a result higher rent-burden coincide with the commonplace of eviction in low-income, minority communities. Examining responses from the Milwaukee Eviction Court study, Desmond (2012) finds that many renters report that their incomes are not much higher than their rents, resulting in high rent to income ratios. Additionally, many do not receive housing assistance.

Desmond and Gershenson (2016b) evaluate individual factors, neighborhood factors, and social network factors that are associated with evictions. At the individual-level, they find that payment history and job loss are significant predictors of eviction. At the neighborhood-level, higher crime rates and higher eviction rates are associated with higher likelihood of eviction. Finally, those that have lower network advantages are at higher risk for eviction. These results suggest that multiple factors can lead to differences in eviction outcomes.

Grief (2018) finds that landlords can use water and nuisance ordinances, which are meant to help protect tenants, to screen for tenant quality and sometimes increase evictions. Kroeger and LaMattina (2020) find that nuisance ordinances can increase eviction filings and eviction judgments by 14 percent.

These papers suggest two broad reasons for the causes of eviction: demographics and economics. Demographic factors include race, ethnicity, gender, and family structure (Desmond, 2012; Desmond et al., 2013; Greenberg et al., 2016; Desmond and Gershenson, 2016b). Economic factors include rent, income, and poverty (Sills et al., 2017; Urban Institute at UNCC, 2018; Desmond and Gershenson, 2016b). The demographic factors are of particular interest because of the possibility of discrimination (Greenberg et al., 2016). However, most of these studies draw these conclusions from studies of urban areas, and, in particular, only a few cities or counties. There is still little understanding as to whether these results hold across the entire US.

Consequences

Eviction is associated with several negative consequences. Hartman and Robinson (2003) find that these include issues with mental health (pp. 468), worse relocation housing (pp. 468), homelessness (pp.468), loss of job, lower educational attainment, poor credit (pp. 469) and potentially violence (pp.470). These consequences are not just negative for the individual, but also for society. The eviction process is costly for communities through court and sheriff costs, as well as costs of aiding the homeless (pp.469). However, these conclusions were drawn from studies that only used local data.

Much of the literature since then has reached the same conclusions. Eviction has been tied to residential instability, which often leads to worse housing outcomes. DeLuca et al. (2019) suggest that moving due to eviction or other housing instability issues does not give families much time to look for new housing. As a result, they end up in the same or worse situations than before. Further, they seem to not know that there are better options. Some suggest that individuals may be less satisfied in their homes, but Johnson and Carswell (2021) do not find those who have been evicted to be more concerned about their housing choice.

One of the primary negative outcomes of housing instability beyond homelessness is its connection to poor health. Burgard et al. (2021) find that renters are more likely to experience depression symptoms if they are behind on rental payments. However, eviction does not seem to be associated with worse self-reported outcomes. Fowler et al. (2015) find that eviction related suicides increased during the Great Recession with suicides taking place before the eviction has even taken place. Eviction has been shown to be connected to sexually transmitted diseases. Groves et al. (2020) find that eviction can increase HIV risk, while Niccolai et al. (2019) find that eviction is associated with higher levels of Chlamydia and Gonorrhea.

An ongoing concern with the COVID-19 pandemic has been the spread of the virus. Although theoretical, Benfer et al. (2020) suggest that COVID-19 can further the spread of the coronavirus and suggest that eviction prevention policies during the pandemic have lowered the spread. The CDC seems to agree as they cite the reason for the federal eviction moratorium being to slow the spread of the virus (CDC, 2020a).

Eviction has been tied to consequences for children. Children who were evicted were twice as likely to be food insecure as children who had not been evicted (Leihfeit et al., 2020). However, there was no sign of a connection between eviction and obesity. Finally, a paper by Teresa and Howell (2020) suggests that eviction and the threat of eviction cause scarcity for housing for some tenants. As a result, new housing subunits are created that may exclude certain tenants.

The majority of the literature suggests that eviction is tied to negative consequences, which confirms the intuitive understanding that eviction has high social costs.

Prevention

Although eviction has been tied to numerous negative consequences, the literature on eviction prevention remains sparse. Only recently have studies focused on methods of reducing or preventing eviction, primarily through existing programs that may have spillovers to eviction. Galagher et al. (2019) suggests that the expansion of Medicaid helped to reduce payment delinquencies, particularly among renters. As missed rental payments are some of the leading causes of eviction, it suggests that eviction may be reduced through the expansion of Medicaid. Zewde et al. (2019) showed that the expansion of Medicaid decreased county-level eviction filing rates and county-level eviction judgment rates. A study by Pilkaukis and Michalemore (2019) suggested that the EITC did not reduce evictions or foreclosures, nor did it prevent homelessness.

Housing interventions have promising outcomes for evictions. A study by Lundberg et al. (2020) finds that public housing does reduce evictions, although other forms of housing support do not. That said, they find that public housing and other forms of housing support, like vouchers, do reduce payment delinquencies. Low Income Housing Tax Credit (LIHTC) properties aimed at seniors have been shown to reduce evictions. Although the study that finds this result, Harrison et al. (2020), does not find a reduction in eviction rates for LIHTC properties for non-seniors. Garcia and Kim (2020) find that families in Rapid Rehousing end up being evited because they are not prepared for the program.

A final method of prevention that has been explored is landlord-tenant laws. Merrit and Farnett (2020) find that states that are tenant friendly have lower eviction rates, suggesting that tenant friendly policies may prevent eviction.

These studies suggest that programs targeted to cost burdened individuals may or may not have an impact on evictions. Other research shows that programs aimed at housing can have positive impacts on eviction or rent delinquency, but also may not be effective for all populations. More work needs to be done on what types of programs best reduce or prevent evictions.

Landlords

In the last few years, researchers have started to focus more on the landlord's role in the eviction process. Qualitative research from Baltimore, MD, Cleveland, OH, and Dallas, TX suggests that landlords prefer a tenant to a vacancy (Garboden and Rosen, 2019). Because an eviction judgment is costly, a landlord will file to reach an eviction judgment only when they believe their tenant will not pay their back rent (Garboden and Rosen, 2019). Qualitative research from Philadelphia, PA suggests that smaller landlords attempt a number of different strategies to avoid eviction outcomes (Balzarini and Boyd, 2020). However, if the tenant is still not able to pay, Balzarini and Boyd (2020) find that landlords often resort to informal eviction methods.

Eviction filings, as opposed to judgments, are less costly to landlords. Eviction filings allow a landlord to reach an eviction judgment if needed. Further, eviction filings can induce a tenant to pay and can give the landlord the opportunity to collect late fees (Garboden and Rosen, 2019). As a result, many landlords will file not to reach an eviction judgment, but simply for the sake of filing to receive any of these benefits.

Raymond et al. (2016) find that larger landlords tend to have higher eviction rates than smaller landlords. Raymond et al. (2018) finds the same result within post foreclosure single family homes. Seymour and Akers (2020) find that large, national landlords have higher eviction rates than smaller properties in Law Vegas, NV. However, large, local landlords have the highest eviction rates. Motels, which often serve as a housing of last resort, are associated with large eviction rates as well. Seymour and Aker (2021) find that post foreclosure single family properties in Detroit, MI that were bought up by large investors see persistently higher eviction rates. Evictions are also more likely in newly constructed units that have higher assess values than the surrounding neighborhood (Robinson and Steil, 2020).

Conclusion

This chapter summarizes landlord-tenant law, the eviction process, and the eviction literature. The overview of landlord-tenant law and the eviction process introduce the reader to the terminology that will be used throughout the rest of the dissertation. Further, it suggests that although landlord-tenant policy differs across states, the eviction process generally does not vary. The review of the literature summarizes the literature to date and establishes a number of gaps in the literature that this dissertation will fill in the following chapters.

There are several limitations to the eviction literature in this chapter. First, the eviction literature is limited in its perspective. Most of the focus of the eviction literature is on the tenant. Although these results are important, eviction is a process that involves two agents: a landlord and a tenant. Because landlords make the decision to file for eviction and begin the eviction process, it is important to have research that includes the landlord's perspective. This dissertation will fill this gap in the literature by developing a theoretical model for the landlord's decision to evict in Chapter III.

Second, the eviction literature is limited by the data. Prior to the Eviction Lab, there was no national database on eviction. As a result, most of the prior literature relies on data from one city or county. For example, seven studies in this chapter use data from Milwaukee, Wisconsin (Desmond, 2012; Desmond et al., 2013; Desmond and Shollenberger, 2015; Desmond et al., 2015; Desmond and Gershenson, 2016a; Desmond and Gershenson, 2016b; Greenberg et al., 2016). Two other studies in this chapter use data from individual counties in North Carolina (Sills et al., 2017; Urban Institute at UNCC, 2018b). Each of these studies focuses on urban areas. As a result, there is no way to know if results from these studies hold across the entire US or even across all urban areas. This dissertation fills this gap in the literature by providing a national study of differences in eviction rates across US counties in Chapter VI.

Third, the eviction literature is limited in the questions it has asked. The literature in this chapter is primarily focused on two topics: the causes of eviction and the consequences of eviction. This dissertation will fill this gap in the literature in Chapters III, V, VI, and Chapter VII all of which address questions previously unanswered in the literature.

CHAPTER III

A THEORETICAL MODEL OF THE EVICTION RATE

To motivate the empirical assessments in later chapters, I develop a theoretical framework for the eviction rate. Eviction results from interactions between landlords and tenants. The decision to evict is made by landlords. This decision may be influenced by factors exogenous to landlords. For example, landlords face tenants who may fall on a continuum of how likely they are to pay back missed rent. If a tenant is more likely to pay back missed rent, landlords may decide to evict less often, whereas if a tenant is less likely to pay back missed rent, landlords may decide to evict more often. Additionally, landlords may be influenced by the economic environment in which they find themselves. Further, a landlords' characteristics, like how large or small they are, may affect their decisions. Ultimately it is the landlords who choose whether to begin the eviction process.

The landlord's decision appears simple: if a tenant does not pay their rent, the landlord files for eviction. However, the literature suggests a more complicated story. As discussed in Chapter II, eviction judgments are costly to landlords (Garboden and Rosen, 2019). Although eviction judgements lead to the removal of a problem tenant, they come with the costs associated with going to court, turning over the unit, and finding a new tenant. Qualitative research from Baltimore, MD, Cleveland, OH, and Dallas, TX suggests that landlords prefer a tenant to a vacancy (Garboden and Rosen, 2019). Qualitative research from Philadelphia suggests that smaller landlords employ a number of strategies to avoid eviction (Balzarinin and Boyd, 2020) Because an eviction judgment is costly, a landlord will file to reach an eviction judgment only when they believe their tenant will not pay their back rent (Garboden and Rosen, 2019).

Although there has been recent literature on the landlord's decision to evict, there has been little theoretical literature on the interactions between landlords and tenants, which affect eviction outcomes. A working paper by Bradford and Bradford (2020) is the only paper to develop a theoretical framework for the study of eviction. Bradford and Bradford (2020) use their model to predict the effect of state and local housing laws on eviction rates. They then test those predictions empirically. Although their model provides useful insight, the game theoretic approach they take complicates their theoretical framework. I take a simpler approach in this chapter.

The Model

Let the county-level eviction rate, *e*, be defined as:

$$e = \frac{Evicted\ ROH}{ROH},$$

where *Evicted ROH* is the county's evicted renter-occupied households and *ROH* is the county's renter-occupied households. I decompose *e* into two parts as follows:

$$e = \left(\frac{ROH\ Hardship}{ROH}\right) \cdot \left(\frac{Evicted\ ROH}{ROH\ Hardship}\right),$$

where $\left(\frac{ROH\ Hardship}{ROH}\right)$ is the share of the county's renter-occupied households that are facing hardship and $\left(\frac{Evicted\ ROH}{ROH\ Hardship}\right)$ is the share of the county's renter-occupied households facing hardship that are evicted.

The prior literature suggests that tenants can experience hardship from an unexpected job loss, car payment, or medical expense. Further, this hardship can lead to difficulty paying rent (Sills et al., 2018). Failure to pay rent is a valid reason to evict a tenant and it is the leading reason why landlords evict their tenant (Sills et al., 2017; McCabe and Rosen, 2020). Additionally, the prior literature suggests that landlords prefer keeping tenants, even those behind on their rent, to evicting tenants (Balzarinin and Boyd, 2019; Garboden and Rosen, 2019). By not immediately evicting tenants, landlords give their tenants the opportunity to catch up on missed rent. Although simplified, the decomposition of *e* into its two components accurately captures the formal eviction rate.

Let the share of the county's renter-occupied households that are facing hardship be defined as:

$$\frac{ROH\ Hardship}{ROH} = r(1-b),$$

where *r* is the probability of a negative shock such as an unexpected job loss, car payment, or medical expense. *b* is the county's support for renter-occupied households who experience a negative shock. I assume that both *r* and *b* are bounded by zero and one, where zero is low and one is high. As *r* increases, the share of the county's renter-occupied households that are facing hardship also increases.

Setting the share of the county's renter-occupied households that are facing hardship equal to *r(1-b)* allows for the potential mitigating effect of the county's support for renter-occupied households who experience a negative shock. As a result, when b=0, the share of the county's renter-occupied households that are facing hardship is equal to *r*. When b=1, the share of the county's renter-occupied households that are facing hardship is equal to zero. Therefore, as *b* increases, the share of the county's renter-occupied households that are facing hardship decreases. In Chapter VII, *r* will be captured by county-level unemployment rates and *b* will be captured by state-level unemployment insurance benefits.

Next, I turn to the landlord's decision. For simplicity, I assume that a landlord can only decide between keeping or evicting their current tenant. This assumption narrows the eviction process to a one step process, instead of a three-step process (file, trial, judgment). The value function for a landlord who has a renter who experiences a negative shock is equal to the higher of two payoffs:

$$V_i(r,b) = \max\{\pi_j, -c + E[\pi(r,b)]\},$$

where π_j is the payoff to the landlord from keeping their current tenant, *j*, and $-c + E[\pi(r,b)]$ is the payoff to the landlord from evicting their current tenant. If the landlord keeps their current tenant, they receive π_j. If the landlord evicts their current tenant, they pay a cost of eviction, *c*, which is bounded between zero (low) and one (high) They then receive a draw of a new tenant from a function that depends on *r* and *b*: $\pi(r, b)$ where the expected payoff is decreasing in *r* and increasing in *b*. $E[\pi(r, b)]$ thus captures the expected payoff to the landlord of a new tenant in the event that the current tenant is evicted. Conditional on *c*, landlords are less likely to evict if they believe their current tenant is better than the tenant pool and are more likely to evict if they believe their current tenant is worse than the tenant pool.

For simplicity, if we think of landlords in a county as being identical, the share of the county's renter-occupied households facing hardship that are evicted can be written as follows:

$$\left(\frac{Evicted\ ROH}{ROH\ Facing\ Hardship}\right) = P\left(\pi_j < -c + E[\pi(r,b)]\right),$$

where *P* indicates probability. Let "tenant quality" be distributed uniformly between 0 and $\frac{1}{R(1-B)}$ and assume that π_j is a random draw from this distribution. The functional form $\frac{1}{R(1-B)}$ is decreasing in *r* and increasing in *b*. With this assumption, the share of the county's renter-occupied households facing hardship that are evicted can written as

$$\left(\frac{Evicted\ ROH}{ROH\ Facing\ Hardship}\right) = F(-c + E[\pi(r,b)]) = \frac{1}{2} - cr(1-b),$$

where $F(\cdot)$ is the uniform cumulative distribution function.

Plugging both parts into our original equation allows for the eviction rate to be written as

$$e = (r(1-b))\left(\frac{1}{2} - cr(1-b)\right)$$

We can take partial derivatives to see how the eviction rate changes as a function of *r* and *b*. The partial derivative of *e* with respect to *r* is

$$\frac{\partial e}{\partial r} = (1-b)\left(\frac{1}{2} - 2cr(1-b)\right)$$

This partial derivative can be positive or negative. By setting this partial derivative equal to or less than zero, we can determine the conditions under which $\frac{\partial e}{\partial r}$ is likely to be negative.

$$(1-b)\left(\frac{1}{2} - 2cr(1-b)\right) \leq 0$$

$$\frac{1}{(1-b)} \leq 4cr$$

Holding *c* and *r* constant, as *b* increases, the left side becomes larger, which makes $\frac{\partial e}{\partial r}$ less likely to be negative. Holding *b* and *c*, as *r* increases, the right side becomes larger, which makes $\frac{\partial e}{\partial r}$ more likely to be negative. Holding *b* and *r*, as *c* increases, the right side becomes larger, which makes $\frac{\partial e}{\partial r}$ more likely to be negative. Therefore, the partial is more likely to be negative, when either *b* is small or when c or *r* is large.

The partial derivative of e with respect to b is:

$$\frac{\partial e}{\partial b} = -r\left(\frac{1}{2} - 2cr(1-b)\right)$$

This partial derivative can be positive or negative. By setting this partial derivative equal to or less than zero, we can determine the conditions under which $\frac{\partial e}{\partial b}$ is likely to be negative.

$$-r\left(\frac{1}{2} - 2cr(1-b)\right) \leq 0$$

$$(1-b) \leq \frac{1}{4cr}$$

Holding c and r constant, as b increases, the left side becomes smaller, which makes $\frac{\partial e}{\partial b}$ more likely to be negative. Holding b and c constant, as r increases, the right side becomes smaller, which makes $\frac{\partial e}{\partial b}$ more likely to be negative. Holding b and r constant, as c increases, the right side becomes smaller, which makes $\frac{\partial e}{\partial b}$ more likely to be negative. Therefore, the partial is more likely to be negative, when either b is large or when c or r is small.

Finally, the cross partial is:

$$\frac{\partial^2 e}{\partial r \partial b} = -\frac{1}{2} + 4cr(1-b)$$

This partial derivative can be positive or negative. By setting this cross partial equal to or less than zero, we can determine the conditions under which $\frac{\partial^2 e}{\partial r \partial b}$ is likely to be negative.

$$-\frac{1}{2}+4cr(1-b)\leq 0$$

$$8(1-b)\leq \frac{1}{cr}$$

Holding *c* and *r* constant, as *b* increases, the left side becomes smaller, which makes $\frac{\partial^2 e}{\partial r \partial b}$ more likely to be negative. Holding *b* and *c* constant, as *r* increases, the right side becomes smaller, which makes $\frac{\partial^2 e}{\partial r \partial b}$ more likely to be negative. Holding *b* and *r* constant, as *c* increases, the right side becomes smaller, which makes $\frac{\partial^2 e}{\partial r \partial b}$ more likely to be negative. Therefore, the partial is more likely to be negative, when either *b* is large or when c or *r* is small.

Conclusion

In this chapter, I develop a theoretical model for the eviction rate. I incorporate both the tenant situation and the landlord decision into the model. I then take the partial and cross partial derivatives to understand the relationship between the Eviction Rate, *e*, the likelihood of a negative shock, *r*, the support for renters, *b*, and the cost of eviction to landlords, *c*.

The partial derivatives reveal a complicated story among *e*, *r*, and *b* in particular. The relationship between *e* and *r* can be either positive or negative. That is, the likelihood of a negative shock can either increase or decrease the eviction rate in the area. This is because the likelihood of a negative shock affects the eviction rate through both the tenant situation and the landlord decision. The likelihood of a negative shock makes a tenant more likely to default on their rent, but if the entire tenant pool is more likely to default on their rent, then the landlord may not want to evict. If the partial is negative, the tenant situation is stronger, if the partial is positive, the landlord decision is stronger.

Similarly, the relationship between e and b can be either positive or negative. That is, the support for renters can either increase or decrease the eviction rate in the area. This is because the support for renters affects the eviction rate through both the tenant situation and the landlord decision. The support for renters may make a tenant less likely to default on their rent, but if the entire tenant pool is less likely to default on their rent, then the landlord may want to evict. If the partial is positive, then the tenant situation is stronger, if the partial is negative, then the landlord decision is stronger.

Finally, the cross partial also reveals a complicated relationship among e, r, and b in particular. The cross partial can be positive or negative. This means that depending on the values of r and b, the Eviction Rate may increase or decrease with changes in r or b.

Overall, this model showcases an important point: because eviction is an outcome in landlord-tenant interactions and because those interactions can be influenced in different ways, we cannot expect a straightforward answer to how certain policies may affect eviction rates. Although it appears straightforward, the relationship is much more complicated than the literature has given it credit for thus far.

CHAPTER IV

EVICTION DATA

Accurately measuring eviction is challenging. The literature uses two types of data most often: administrative data or survey data. Both types have their shortcomings. Survey data is limited in that it can undercount the prevalence of rental housing evictions or it can fail to capture a complete picture of housing displacement (Lundberg and Donnelly, 2018; Porton et al., 2020). As a result, many researchers use administrative data. However, administrative data is limited in that it does not capture informal evictions and can contain errors (Lundberg and Donnelly, 2018; Porton et al., 2020). Porton et al (2020) argue that administrative data can overcome its shortcomings by careful cleaning of the dataset.

My data for eviction come from the Eviction Lab, the first national database on eviction in the United States. Created by Matthew Desmond and his team out of Princeton University, the Eviction Lab provides the first look at eviction across the nation. By gathering and standardizing data from across the United States, the Eviction Lab fills a huge gap in the data on evictions. The Eviction Lab website states that “Researchers can use the data to help us document the prevalence, causes, and consequences of eviction and to evaluate laws and policies designed to promote residential security and reduce poverty” (The Eviction Lab, 2018). The database gives researchers the opportunity to study questions that were previously impossible to study due to data limitations.

Since its release, peer-reviewed studies and working papers have relied on the Eviction Lab database for their data (Bradford and Bradford, 2019; Zewde et al., 2019; Merritt and Farnworth, 2020; Bradford and Bradford, 2020). However, there have been a number of critiques of the database. One of the most common being that the Eviction Lab undercounts the number of evictions in certain localities (Aiello et al., 2018). The critiques of the database necessitate an establishment of the quality of the database as a primary source for documenting evictions in the United States, either nationally or at the state or local level. This chapter provides an explanation of the Eviction Lab database, discusses the measure of eviction that will be used in the analyses in later chapters, and assesses the quality of the Eviction Lab data.

The Eviction Lab

The Eviction Lab contains estimates of eviction filings and eviction judgements at the Census block group-, Census tract-, city-, county-, state-, and national-level for 2000-2016. Because my research will use the county-level and state-level estimates, I will focus on these estimates going forward. The county-level (state-level) estimates were primarily produced by cleaning, merging, and aggregating individual-level civil court cases from LexisNexis Risk Solutions (LexisNexis), American Information Research Services Inc. (AIRS), and local courts. Compiled data were validated against state reported county-level court statistics whenever possible. The data were standardized to 2010 Census geographical boundaries and linked to Census and American Community Survey data on population, renter population, rent, property value, income, poverty, and race. Although the database is the most comprehensive to date, it captures only formal evictions, which means it underestimates the prevalence of eviction in the United States (Desmond et al., 2018b).

Measuring Eviction

The Eviction Lab data includes four measures of eviction: eviction filings, eviction judgements, the eviction filing rate, and the eviction judgement rate[1]. The eviction filings variable

[1] What I refer to as "eviction judgments" the Eviction Lab calls "evictions" and what I refer to as the "eviction judgment rate" the Eviction Lab calls the "eviction rate".

is the number of eviction filings in a county (state) per year, including multiple eviction filings against the same address. The eviction judgments variable is the number of eviction judgements in a county (state) per year. The eviction filing rate variable is the number of eviction filings over the number of renter-occupied households in a county (state) per year. Finally, the eviction judgment rate variable is the number of eviction judgments over the number of renter-occupied households in county (state) per year.

Although each of these four measures is informative, my analysis relies on the eviction filing rate and the eviction rate. Accounting for the number of renter-occupied households is crucial for comparisons across the nation and over time, because it standardizes my measures of eviction. If I did not control for the number of renter-occupied households, I would not know if changes in eviction were due to more evictions or more renters. The eviction filing rate and the eviction judgment rate provide two good measures for understanding differences across regions and over time.

Because eviction filings do not always turn into eviction judgements, I construct a fifth measure of eviction: the likelihood of eviction. I define it as follows:

$$Likelihood\ of\ Eviction = \frac{\#\ of\ eviction\ judgements}{\#\ of\ eviction\ filings}$$

This measure is the proportion of eviction filings that turn into eviction judgments, that is, the likelihood that an eviction filing becomes an eviction judgement.

I believe the likelihood of eviction is useful measure because it captures the potential of going through the entire eviction process, as opposed to experiencing each part individually. This measure tells me how likely it is that eviction filings turn into eviction judgements. When comparing eviction across regions and over time, it is important to see the difference in the likelihood of going through the entire eviction process. An eviction filing in and of itself carries weight for renters, but an eviction filing in an area with a higher likelihood of eviction carries even more weight, because it increases the likelihood of experiencing the worst of eviction's negative consequences: removal from the home.

Missing Data

The Eviction Lab contains data for 3,144 counties[2]. Of those 3,144 counties, all but one (Clifton Forge City, VA) appears in the database from 2000-2016. As a result, the database contains 53,436 county-year observations. However, eviction estimates are missing for certain counties in certain years. Coverage gaps exist because either the data was unable to be collected or the data was dropped. For the former, eviction data in some regions is not collected, reported, or may be sealed (Desmond et al., 2018b). For the latter, eviction data was deemed unreliable by the Eviction Lab researchers. Furthermore, counties needed to have at least two consecutive data points to be included in the database. This means that a county needed to appear in two years back-to-back for it to contain an eviction estimate. Unfortunately, I am not able to determine whether a missing value is the result of a true missing or of dropped data. In total, the Eviction Lab contains estimates for eviction filings (and the eviction filing rate) for 2,972 counties over time, which results in 44,168 county-year observations. It contains estimates for eviction judgments (and the eviction judgment rate) for 2,759 counties over time, which results in 41,339 county-year observations.

Substitution. Some of the estimates in the Eviction Lab have been substituted from sources other than LexisNexis, because LexisNexis was incomplete for the following states: New Jersey, Alaska, Arkansas, North Dakota, and South Dakota, as well as Pennsylvania for the years 2007 to 2016. The New Jersey data was missing outcomes on its individual-level court cases. The

[2] I focus on the county-level data because the county-level data is aggregated to create the state-level data. As a result, any missing data issue at the county-level affects the missing data at the state-level.

Eviction Lab updated these outcomes by merging data from AIRS on to the LexisNexis data (Desmond et al., 2018b). Alaska, Arkansas, North Dakota, and South Dakota did not have consistent data coverage on eviction filings or eviction judgements. As a result, the Eviction Lab substituted state-reported court statistics for these states and adjusted them by a factor[3] (Desmond et al., 2018b). Lastly, Pennsylvania data was missing from 2007 to 2016. The Eviction Lab filled in the missing data with individual-level data from the Pennsylvania courts, again adjusting them by a factor (Desmond et al., 2018b).

All estimates that were substituted are flagged in the database as "subbed". There is a total of 4,461 county-year observations that are "subbed". These observations make up 8.35 percent of the county-level data. The Eviction Lab standardized the data the best they could across all four data sources. As a result, I will not adjust for or drop the "subbed" data in my samples.

Imputation. Some of the estimates in the Eviction Lab have been imputed. The rules for imputation were as follows. They did not impute prior to the first good value or after the last good value except for 2016 in which case they imputed the 2016 value with the 2015 value. For missing data between the first and last good values, if only one or two consecutive values were missing, they imputed values using linear interpolation. If more than two consecutive values were missing, they did not impute any values. Counties that had more data missing were not imputed.

All estimates that were imputed are flagged in the database as "imputed". There is a total of 612 county-year observations that are "imputed". These observations make up 1.15 percent of the county-level data. The Eviction Lab made logical imputation choices. As a result, I will not adjust for or drop the "imputed" data in my samples.

[3] The Eviction Lab created their adjustment factor by comparing their data to state reported court statistics for landlord-tenant cases, as well as taking into consideration the housing market a state was in.

Data Quality

To understand how the missing data at the county-level impacts the coverage of the state-level data, I pulled the county extracts from 2000-2016. I flagged all counties that reported eviction filings (eviction filings ≥ 0) and eviction judgements (eviction judgements ≥ 0). First, I aggregated the flagged counties for each state and divided the aggregation by the number of counties in the state. The result is the percentage of counties in the state that reported eviction filings and eviction judgements, respectively. I present the percentage of counties in the state that reported eviction filings in Table 4.1, because the results are the same across both tables except in states that report eviction filings and not eviction judgments (Alaska, Arkansas, North Dakota, and South Dakota). That is, if a state reports a certain percentage of counties reporting eviction filings, the same percentage of counties report eviction judgements, except in Alaska, Arkansas, and North and South Dakota, where no eviction judgements are reported.

Table 4.1 confirms that not every eviction filing (or eviction judgement) is recorded in the Eviction Lab. Reporting has two trends: consistency and completeness. Consistency represents how similar each state's reporting is in each year, while completeness represents how many of the counties report in each year. Some states have both trends, while others have one or the other, while still others have neither of the trends. For example, Alabama has consistent, but incomplete reporting across all years, while Alaska has inconsistent and incomplete data. Notice that 2000 and 2001 tend to be less consistent and complete than the rest of the data sets, even in states that tend to have better reporting. Because there is inconsistent and incomplete data, it is important to understand what the given data tell us about eviction in every state.

Table 4.1.

Percentage of Counties Reporting Eviction Filings over Time by State

	Year																
State	00	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16
AL	64	99	99	97	93	91	93	97	97	97	97	97	97	97	97	97	97
AK	0	0	0	0	0	0	0	0	100	100	100	100	100	100	100	100	100
AZ	100	100	100	100	100	87	67	47	40	40	33	33	33	40	40	40	40
AR	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
CA	78	84	86	84	83	81	76	81	81	83	79	69	66	64	67	62	66
CO	73	81	86	88	86	88	88	88	86	84	92	86	78	73	72	73	86
CT	0	38	25	25	25	38	38	38	38	38	38	38	38	38	38	75	75
DE	67	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
DC	0	0	0	0	0	0	100	100	100	100	100	100	100	0	0	0	100
FL	57	72	82	82	81	81	84	82	82	82	84	84	85	87	87	87	88
GA	55	65	71	80	78	79	75	74	74	73	78	79	78	81	82	84	86
HI	100	80	80	80	80	80	60	60	60	40	20	20	20	40	60	60	60
ID	80	91	93	95	93	93	93	93	93	91	91	91	91	93	93	91	91
IL	74	91	98	99	98	98	96	96	96	95	96	96	95	95	91	89	90
IN	50	68	84	83	88	88	86	78	78	79	88	89	89	91	92	88	91
IA	71	96	96	96	96	96	96	97	97	97	96	96	96	96	97	97	97
KS	86	95	97	97	100	100	100	100	100	100	100	100	99	98	97	96	96
KY	69	80	88	88	84	82	81	79	78	78	82	83	83	83	81	78	78
LA	30	50	56	59	59	59	61	59	58	53	53	53	53	50	42	42	47

ME	19	50	88	94	94	94	94	100	100	100	100	100	100	100	100	100	100
MD	13	13	17	21	21	21	29	29	29	33	25	25	25	25	25	13	13
MA	0	29	50	43	36	50	50	57	86	86	93	93	93	93	100	100	100
MI	30	39	82	90	90	98	96	95	95	98	98	99	99	95	94	93	94
MN	46	57	69	69	71	75	76	76	78	82	83	83	90	95	94	94	94
MS	74	77	74	78	80	83	83	80	89	89	88	87	87	87	88	83	83
MO	67	78	85	90	94	95	100	100	100	100	100	100	100	97	97	88	88
MT	86	88	88	89	88	91	89	89	89	89	91	93	95	95	95	95	95
NE	82	92	92	92	92	92	92	92	92	92	92	92	92	92	92	94	94
NV	82	88	76	71	76	71	65	71	71	82	94	94	94	94	94	88	88
NH	0	0	0	0	10	60	90	90	90	90	80	60	60	60	60	20	20
NJ	0	100	100	90	90	90	100	100	100	100	100	100	100	100	100	100	100
NM	88	94	100	97	94	94	85	85	85	79	76	70	70	70	64	55	61
NY	31	31	31	29	31	32	35	32	32	32	34	37	39	40	44	44	47
NC	63	79	87	89	84	90	90	90	91	92	92	92	92	92	92	92	92
ND	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
OH	33	84	95	94	93	93	95	95	97	97	98	99	99	99	99	99	99
OK	71	92	95	95	96	96	97	96	96	96	97	97	97	97	97	97	97
OR	64	97	100	100	100	100	100	100	100	100	97	94	92	92	92	92	92
PA	99	99	100	100	100	100	100	93	93	93	100	100	100	100	100	100	100
RI	0	20	0	0	0	0	0	60	60	60	60	60	40	40	40	80	80
SC	0	0	0	0	0	0	0	0	0	57	98	100	100	98	96	85	85
SD	0	0	0	0	0	0	0	0	0	0	85	85	85	85	85	85	85

TN	72	88	93	96	94	84	83	83	76	66	66	67	75	68	62	63	64
TX	70	82	83	84	86	86	85	85	85	84	85	86	86	85	82	81	81
UT	69	83	86	86	86	86	93	97	97	100	100	100	100	100	100	100	100
VT	79	86	86	86	86	86	86	86	86	86	79	79	79	79	79	79	79
VA	89	93	95	97	98	98	98	89	89	88	90	92	91	92	91	92	92
WA	82	95	95	87	79	79	77	74	69	72	67	62	62	62	67	77	82
WV	44	71	60	71	73	71	73	85	91	93	93	95	95	96	96	98	98
WI	79	93	99	97	97	97	99	100	100	100	100	100	100	100	100	100	100
WY	65	65	70	74	74	74	74	74	74	74	70	65	65	65	65	65	65

Next, I study what percentage of the renter-occupied households in the state are represented by the counties that were reporting eviction filings. If a state has all but one county reporting eviction filings, but that one county contains most of the renter population, then the evictions we see may not be an accurate representation of eviction levels across the state. That is, the inconsistent and incomplete data reporting is only an issue that needs to be corrected if it does not give us an accurate picture of eviction in a state. I aggregated the number of renter-occupied households in the state from counties that reported eviction filings. I divided that number by the total number of renter-occupied households in the state. The result is the percentage of renter-occupied households in the state that are represented by the counties representing eviction filings, which is shown in Figure 4.1.

Once again, some states have data that is much more representative of their renter households, and therefore of their eviction filings, than others. Alaska and Hawaii both have inconsistent data, while Alaska's is also incomplete. Because both states are not within the continental United States, their housing markets will differ more than the rest of the United States. As a result, I drop Alaska and Hawaii from the rest of the data analyses. Furthermore, because DC is not a state or a county and it does not have consistent data coverage, I also drop DC from the rest of the analyses. These graphs also confirm that the data in 2000 and 2001 tends to be less consistent and complete across all states. As a result, I drop 2000 and 2001 from the rest of the data analyses to have more consistent coverage across time.

Figure 4.1 Renter Households Represented by State, 2000-2016

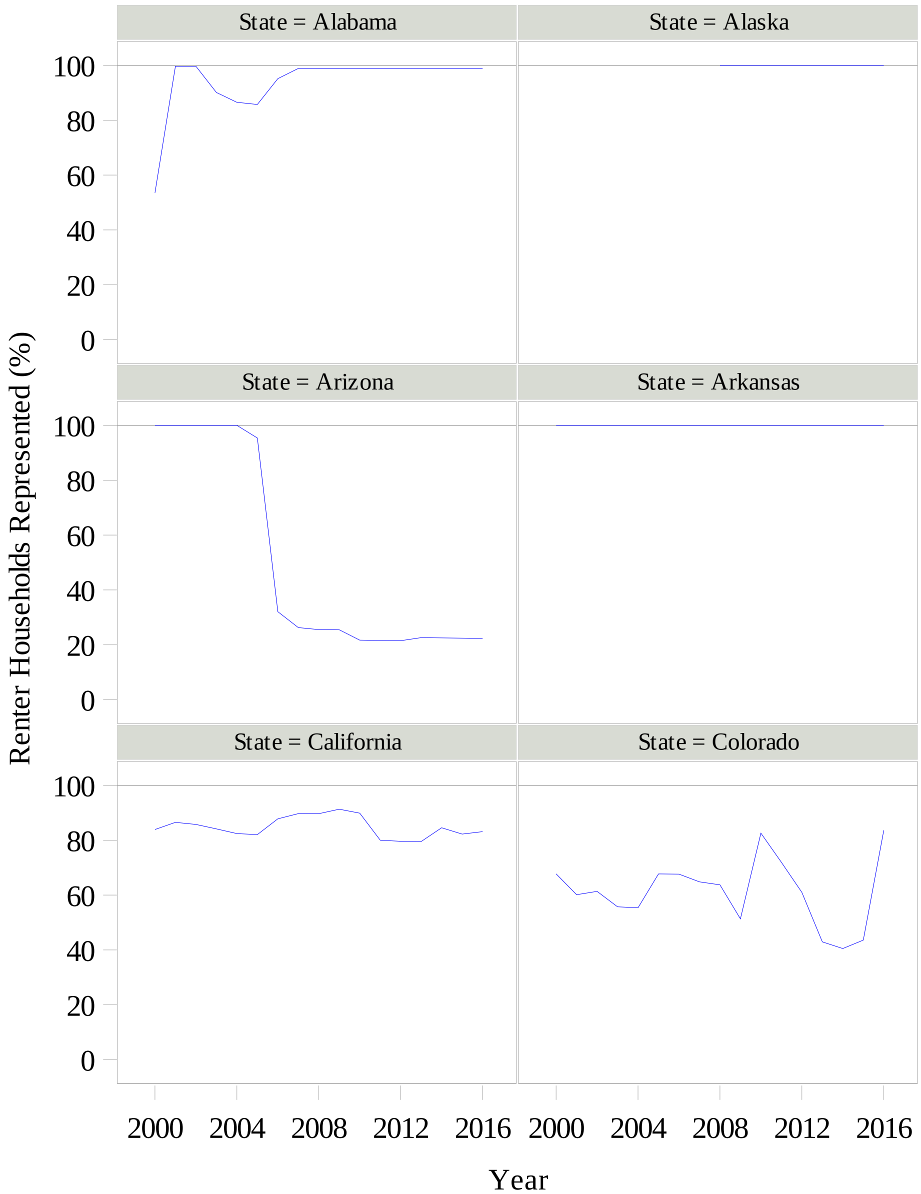


Figure 4.1 Renter Households Represented by State, 2000-2016

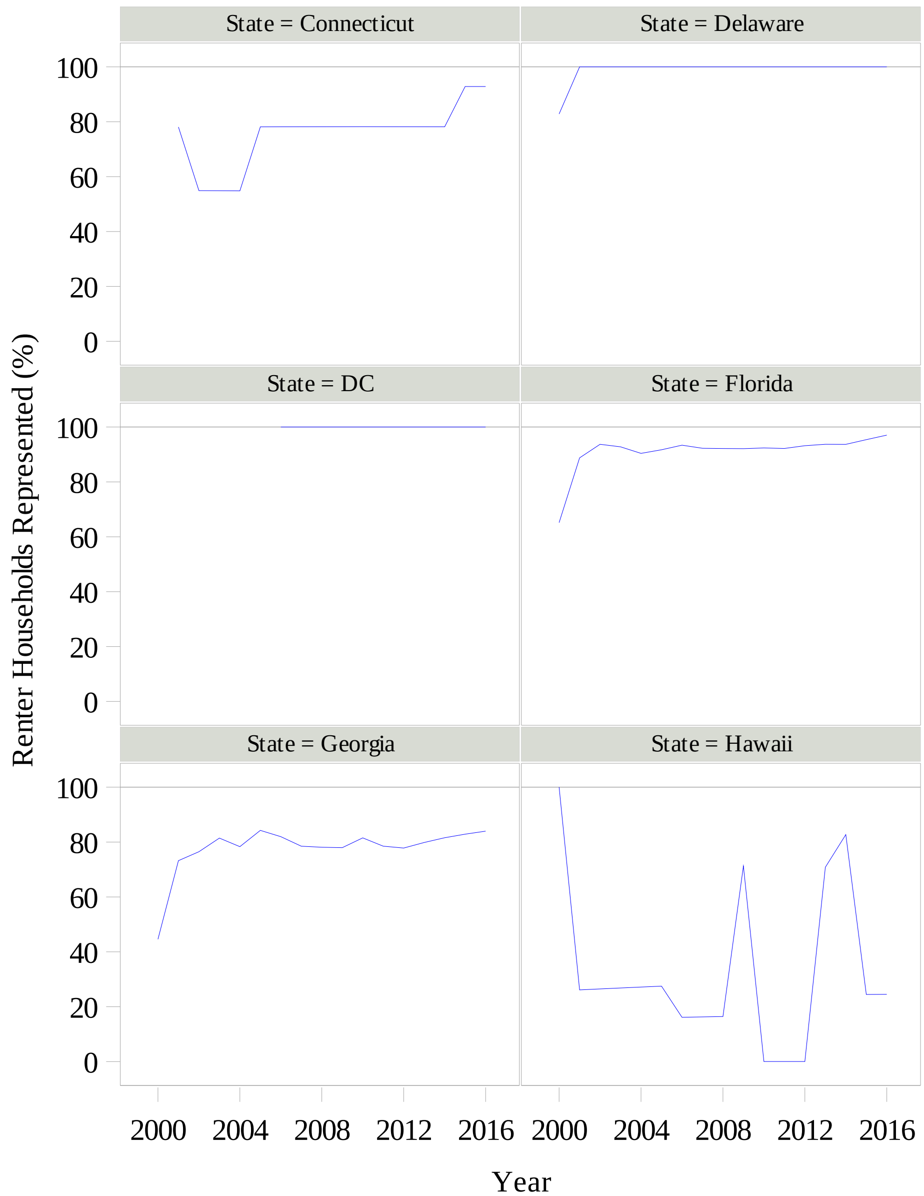


Figure 4.1 Renter Households Represented by State, 2000-2016

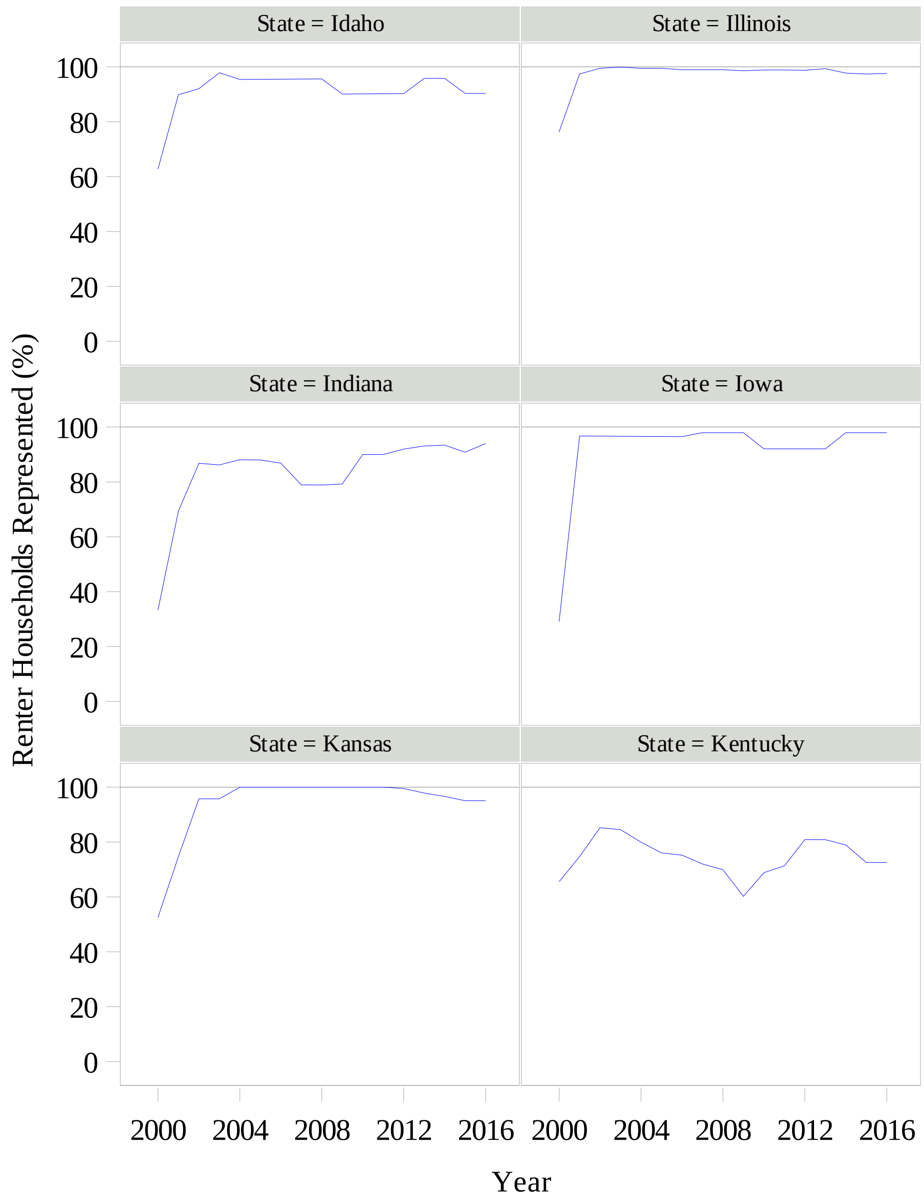


Figure 4.1 Renter Households Represented by State, 2000-2016

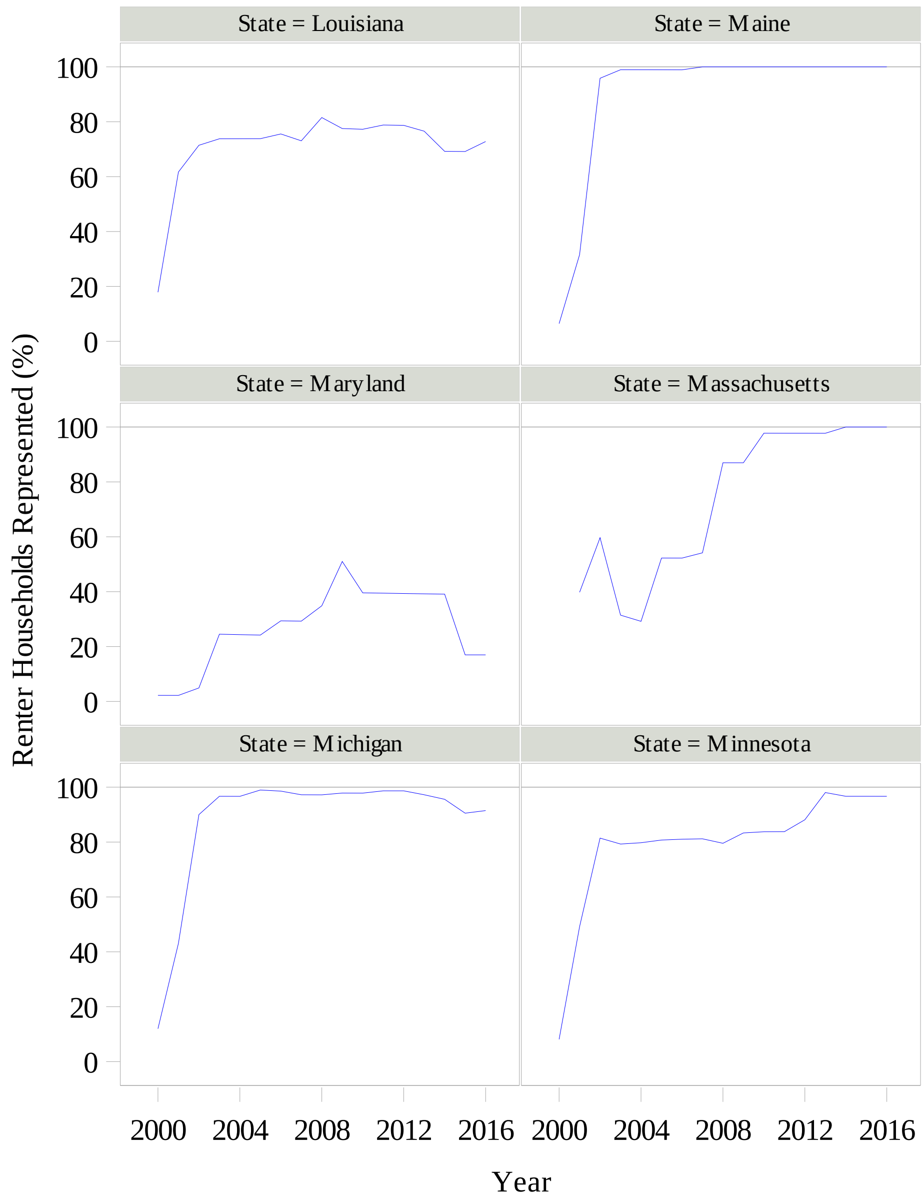


Figure 4.1 Renter Households Represented by State, 2000-2016

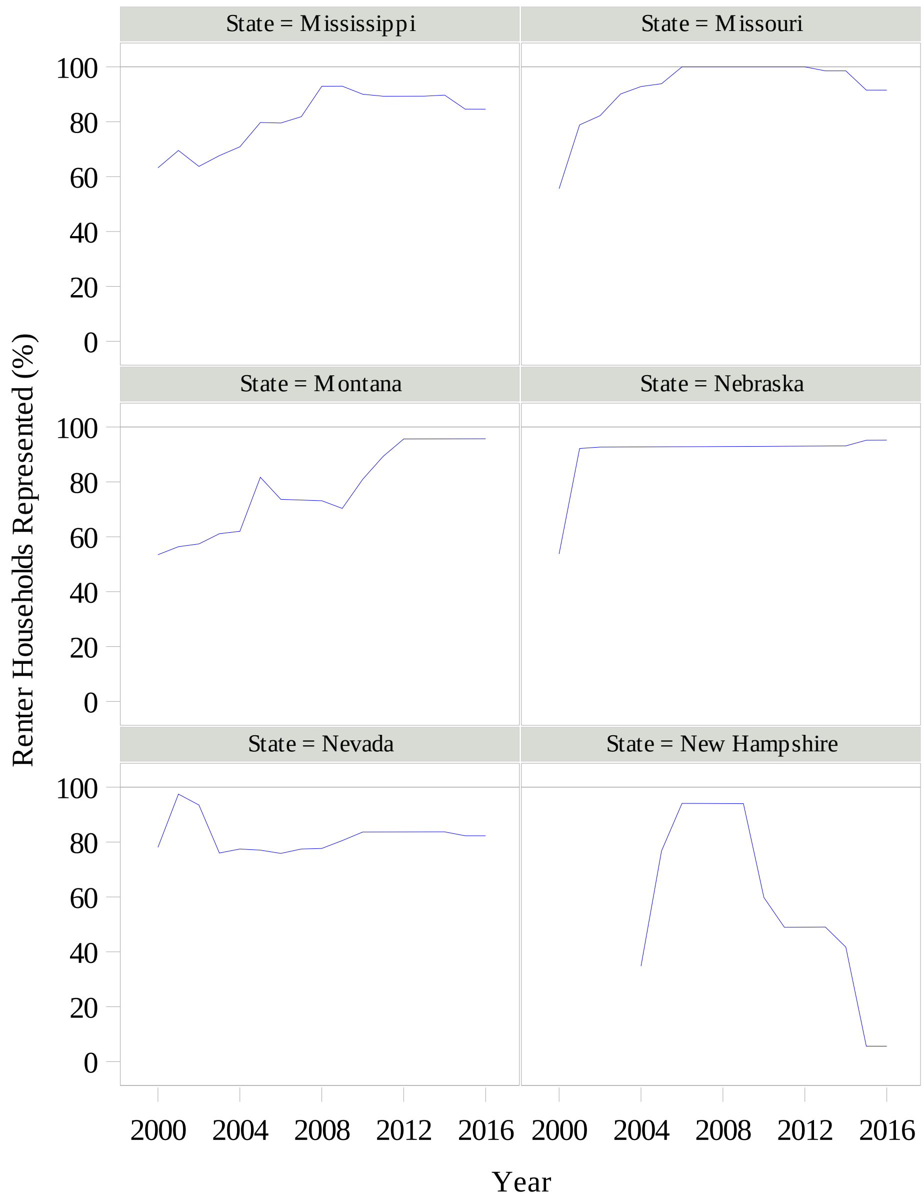


Figure 4.1 Renter Households Represented by State, 2000-2016

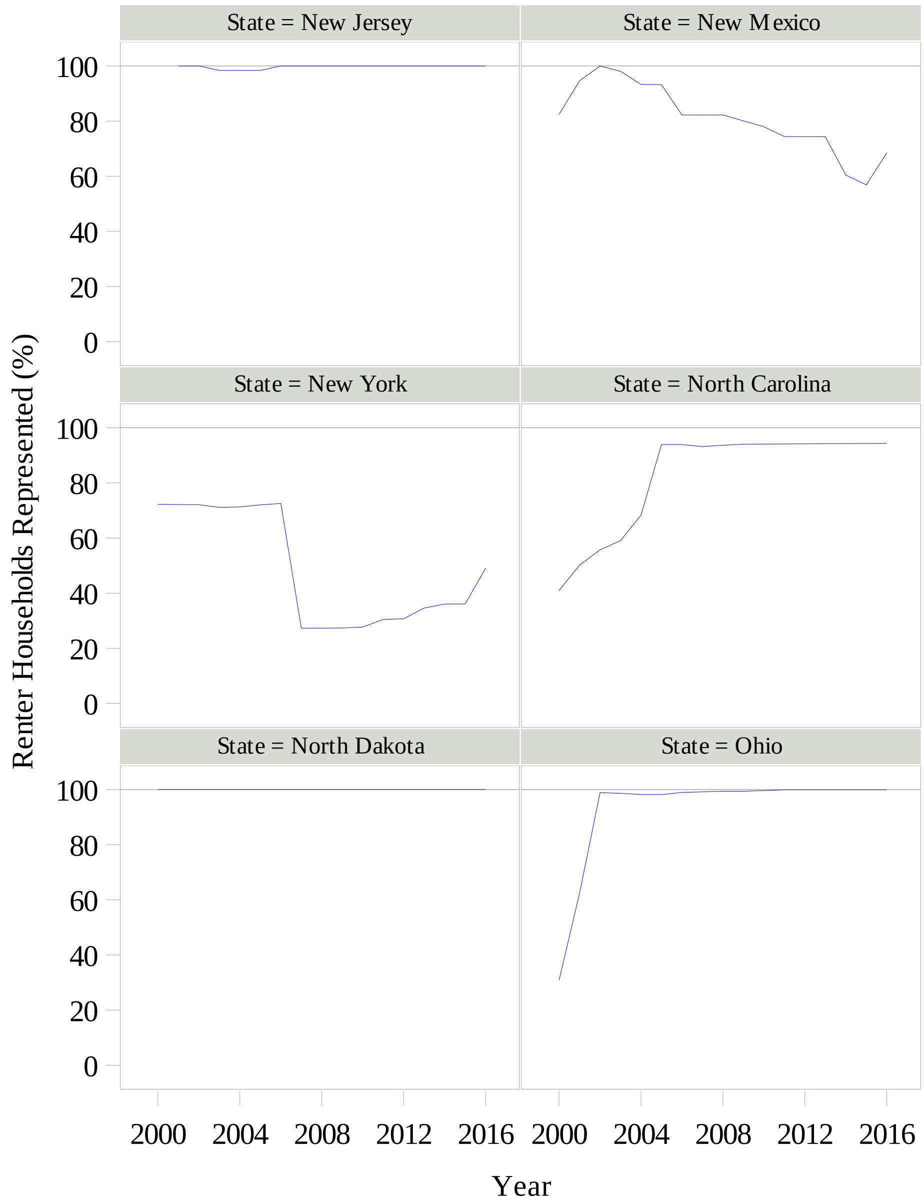


Figure 4.1 Renter Households Represented by State, 2000-2016

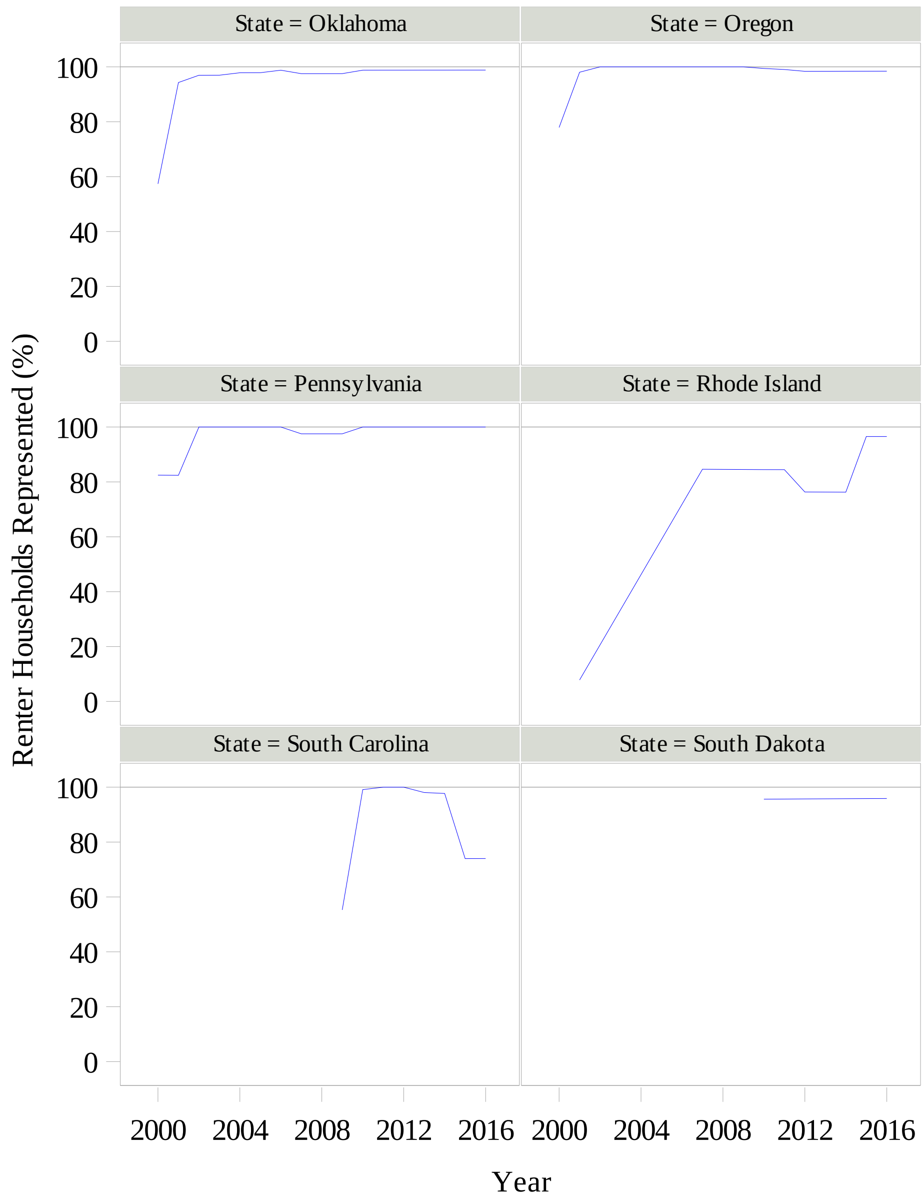


Figure 4.1 Renter Households Represented by State, 2000-2016

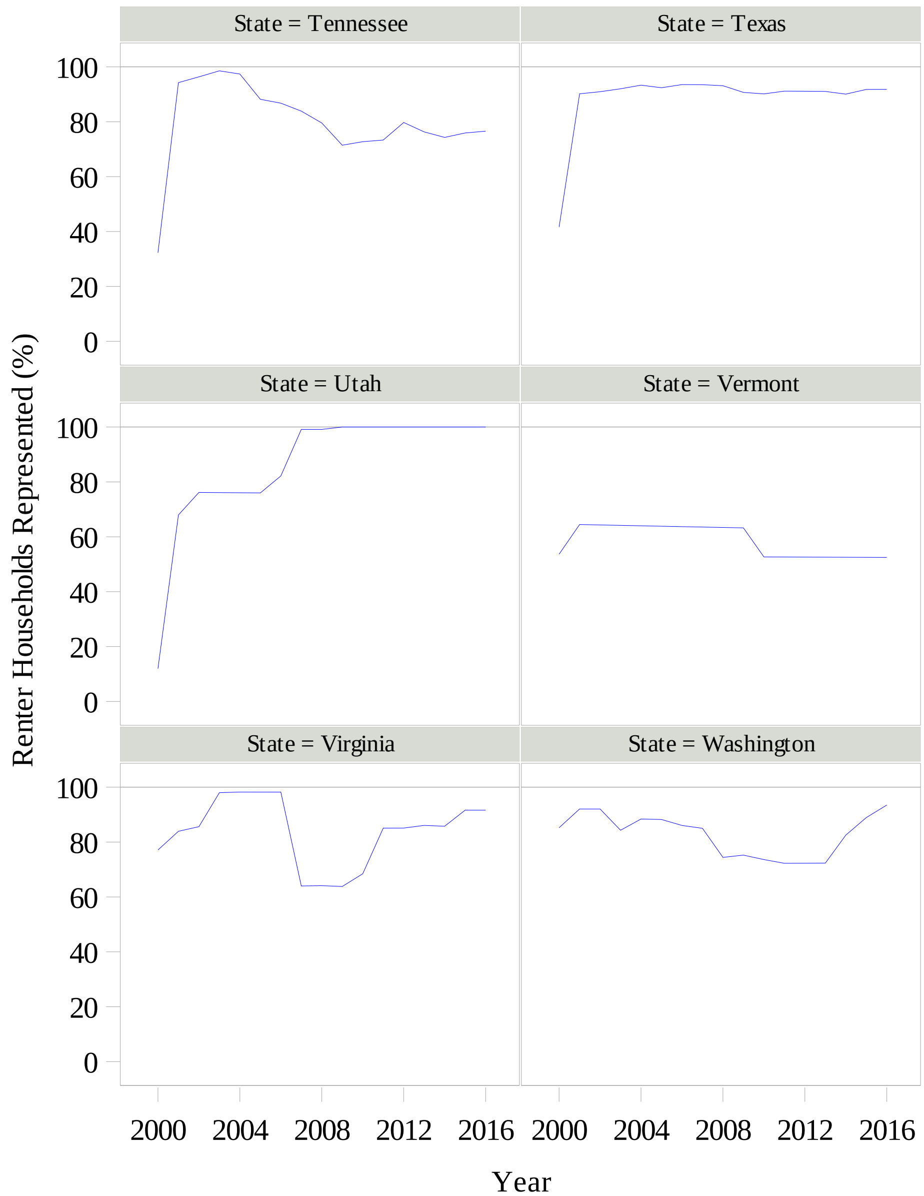
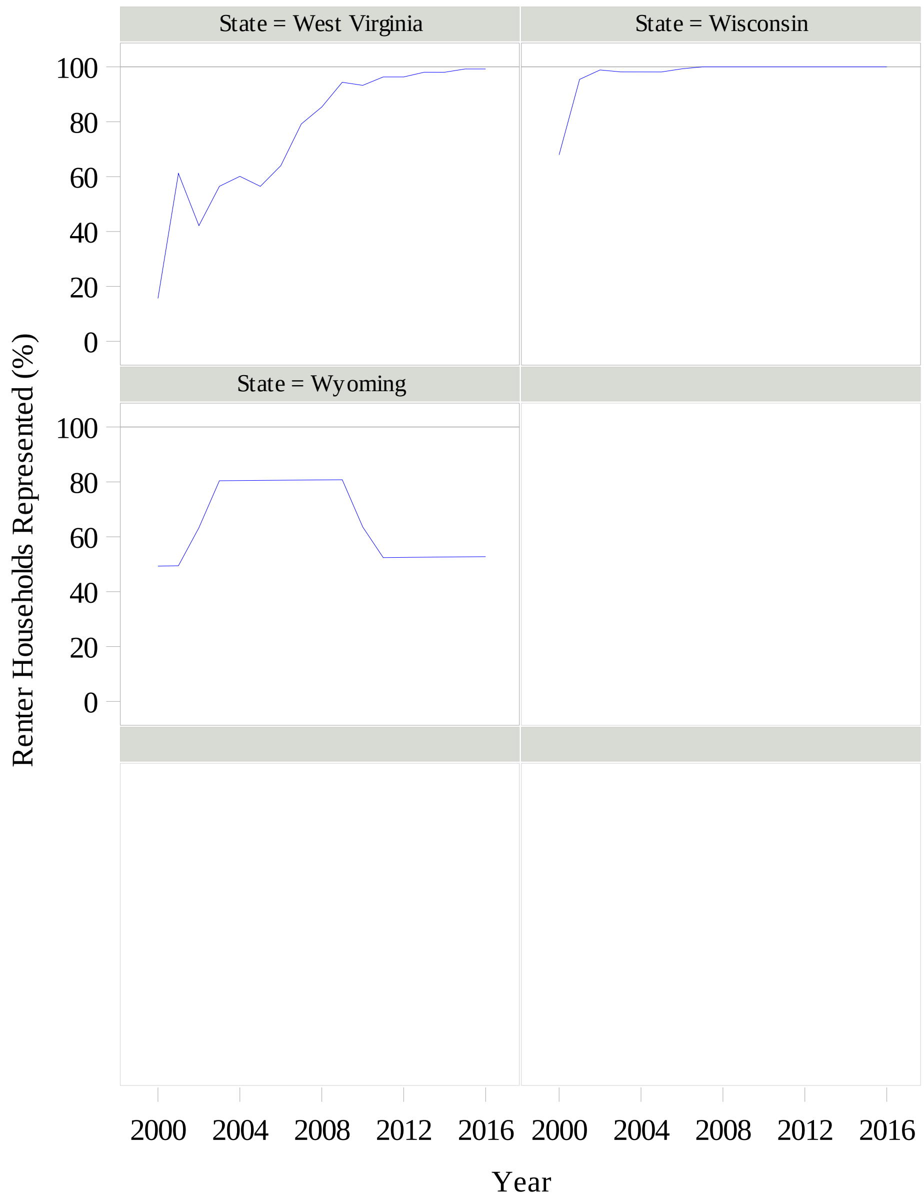


Figure 4.1 Renter Households Represented by State, 2000-2016



The inconsistent and incomplete data does provide some states with better or worse quality data. If all states were included in a state-level analysis, then they would not provide an accurate picture of eviction across the United States. To adjust for this fact, I develop a data quality variable, which captures the consistency and completeness of each state's data.

I begin with the renters reporting variable. This variable captures the percentage of renters represented by counties reporting eviction filings. I use this measure to construct a data quality variable. Using the distribution of the renters reporting variable, I created categories for high, medium, and low reporting of eviction filings. Reporting above the median value was considered high quality data and was assigned a value of one, while any reporting that was between the first quartile and the median value was considered medium quality and assigned a value of two. Any reporting that was in the first quartile was considered low quality and was assigned a value of three. Each state received a data quality score for each year, which is shown in Table 4.2.

Table 4.2
Data Quality Scores over Time by State

	Year															Data Quality
State	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	Mean
AL	1	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1.2
AK	3	3	3	3	3	3	1	1	1	1	1	1	1	1	1	1.8
AZ	1	1	1	1	3	3	3	3	3	3	3	3	3	3	3	2.5
AR	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
CA	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
CO	3	3	3	3	3	3	3	3	2	3	3	3	3	3	2	2.9
CT	3	3	3	2	2	2	2	2	2	2	2	2	2	1	1	2.1
DE	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
DC	3	3	3	3	1	1	1	1	1	1	1	3	3	3	1	1.9
FL	1	1	2	2	1	1	1	1	1	1	1	1	1	1	1	1.1
GA	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
HI	3	3	3	3	3	3	3	3	3	3	3	3	2	3	3	2.9
ID	1	1	1	1	1	1	1	2	2	2	2	1	1	2	2	1.4
IL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
IN	2	2	2	2	2	2	2	2	2	2	2	1	1	2	1	1.8

IA	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1.1
KS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
KY	2	2	2	3	3	3	3	3	3	3	2	2	2	3	3	2.6
LA	3	3	3	3	3	3	2	2	2	2	2	2	3	3	3	2.6
ME	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
MD	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
MA	3	3	3	3	3	3	2	2	1	1	1	1	1	1	1	1.9
MI	2	1	1	1	1	1	1	1	1	1	1	1	1	2	2	1.2
MN	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	1.7
MS	3	3	3	2	2	2	1	1	2	2	2	2	2	2	2	2.1
MO	2	2	1	1	1	1	1	1	1	1	1	1	1	2	2	1.3
MT	3	3	3	2	3	3	3	3	2	2	1	1	1	1	1	2.1
NE	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
NV	1	3	2	2	3	2	2	2	2	2	2	2	2	2	2	2.1
NH	3	3	3	2	1	1	1	1	3	3	3	3	3	3	3	2.4
NJ	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
NM	1	1	1	1	2	2	2	2	2	3	3	3	3	3	3	2.1
NY	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
NC	3	3	3	1	1	1	1	1	1	1	1	1	1	1	1	1.4
ND	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
OH	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
OK	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
OR	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
PA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
RI	3	3	3	3	3	2	2	2	2	2	2	2	2	1	1	2.2
SC	3	3	3	3	3	3	3	3	1	1	1	1	1	3	3	2.3
SD	3	3	3	3	3	3	3	3	1	1	1	1	1	1	1	2.1
TN	1	1	1	2	2	2	2	3	3	3	2	2	3	3	2	2.1
TX	2	2	1	1	1	1	1	2	2	2	2	2	2	2	2	1.7
UT	2	2	3	3	2	1	1	1	1	1	1	1	1	1	1	1.5
VT	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
VA	2	1	1	1	1	3	3	3	3	2	2	2	2	2	2	2

WA	1	2	2	2	2	2	3	3	3	3	3	3	2	2	1	2.3
WV	3	3	3	3	3	2	2	1	1	1	1	1	1	1	1	1.8
WI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
WY	3	2	2	2	2	2	2	2	3	3	3	3	3	3	3	2.5

There are 8 states that have low data quality using this measure. They are Colorado, Hawaii, Kentucky, Louisiana, Maryland, New York, Vermont, and Wyoming. There are 19 states that have medium quality data and 21 states that have good comprehensive data. Over half of the states do not have good quality data, which is a lot when trying to establish national trends and differences in eviction filing and eviction judgments across states.

The Eviction Lab does recognize that there are gaps in their data. The Eviction Lab verified their estimates against outside sources whenever possible. They produced a variable in the data set that flags areas where the Eviction Lab researchers believe measures of eviction have been undercounted. The variable is equal to 1 if the if the Eviction Lab researchers believe the filings reported are undercounted, while its equal to 0 if they do not believe the filings are undercounted. I compare my data quality measure against the Eviction Lab's data quality measure to determine comparability, which is shown in Table 4.3.

Table 4.3
Comparison of Quality Measures: Constructed versus Eviction Lab

State	Data Quality	Low Flag
AL	High	0.00
AK	Medium	1.00
AZ	High	0.00
AR	Medium	1.00
CA	Low	0.00
CO	Medium	1.00
DE	High	0.00

FL	High	0.00
GA	Medium	0.00
ID	High	1.00
IL	High	0.00
IN	Medium	0.00
IA	High	0.00
KS	High	0.00
KY	Low	1.00
LA	Low	1.00
ME	High	0.00
MD	Low	1.00
MA	Medium	0.00
MI	High	0.00
MN	Medium	0.00
MS	Medium	0.00
MO	High	0.00
MT	Medium	0.00
NE	High	0.00
NV	Medium	0.00
NH	Medium	1.00
NJ	High	1.00
NM	Medium	0.00
NY	Low	1.00
NC	High	0.00
ND	High	0.00
OH	High	0.00
OK	High	0.00
OR	High	0.00
PA	High	0.00
RI	Medium	0.00
SC	Medium	0.00
SD	Medium	0.00

TN	Medium	1.00
TX	Medium	1.00
UT	High	0.00
VT	Low	1.00
VA	Medium	0.00
WA	Medium	1.00
WV	Medium	0.00
WI	High	0.00
WY	Low	1.00

As shown in Table 4.3, the two measures do not always agree. For example, my measure finds Colorado to have low quality data, but Eviction Lab does not flag it as “low”. The same goes for Idaho and New Jersey. My measure finds these states to have high c quality data, but the Eviction Lab has them flagged as low. This results from the Eviction Lab comparing their estimates to state-reported county statistics.

To capture all possible strays from good data quality, I construct an adjusted quality score. I adjust the quality score by adding my initial data quality score values to the low flag value. If the adjusted data quality score remained at one it was still considered high quality, if a quality score dropped to or remained at two it was considered medium quality, if a quality score dropped to or remained at three or dropped to four it was considered low quality.

I created an average score for each state by averaging each state’s quality score over time and rounding to the closest integer. Each state’s adjusted quality score in each year, as well as its average score is shown in Table 4.4. As shown, there are 19 states (39.6%) that report high quality data, 16 states (33.3%) that report medium quality data, and 13 states (27.1%) that report low quality data. In the next chapter, I study the extend of the US eviction crisis, which requires accurate information on eviction filings and evictions. As a result, I will restrict my sample in that Chapter by data quality for most of the analyses.

Table 4.4
Adjusted Data Quality Scores over Time by State

	Year															Data Quality Score
State	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	Average
AL	1	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1
AZ	2	2	2	2	4	4	4	4	4	4	4	4	4	4	4	3
AR	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
CA	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
CO	3	3	3	3	3	3	3	3	2	3	3	3	3	3	2	3
CT	4	4	4	3	3	3	3	3	3	3	3	3	3	2	2	3
DE	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
FL	1	1	2	2	1	1	1	1	1	1	1	1	1	1	1	1
GA	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
ID	2	2	2	2	2	2	2	3	3	3	3	2	2	3	3	2
IL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
IN	2	2	2	2	2	2	2	2	2	2	2	1	1	2	1	2
IA	1	1	1	1	1	1	1	1	1	1	1	2	1	1	1	1
KS	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
KY	3	3	3	4	4	4	4	4	4	4	3	3	3	4	4	4
LA	4	4	4	4	4	4	3	3	3	3	3	3	4	4	4	4
ME	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
MD	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
MA	3	3	3	3	3	3	2	2	1	1	1	1	1	1	1	2
MI	2	1	1	1	1	1	1	1	1	1	1	1	1	2	2	1
MN	2	2	2	2	2	2	2	2	2	2	2	1	1	1	1	2
MS	3	3	3	2	2	2	1	1	2	2	2	2	2	2	2	2
MO	2	2	1	1	1	1	1	1	1	1	1	1	1	2	2	1
MT	3	3	3	2	3	3	3	3	2	2	1	1	1	1	1	2
NE	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
NV	1	3	2	2	3	2	2	2	2	2	2	2	2	2	2	2

NH	4	4	4	3	2	2	2	2	4	4	4	4	4	4	4	3
NJ	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
NM	1	1	1	1	2	2	2	2	2	3	3	3	3	3	3	2
NY	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
NC	3	3	3	1	1	1	1	1	1	1	1	1	1	1	1	1
ND	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
OH	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
OK	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
OR	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
PA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
RI	3	3	3	3	3	2	2	2	2	2	2	2	2	1	1	2
SC	3	3	3	3	3	3	3	3	1	1	1	1	1	3	3	2
SD	3	3	3	3	3	3	3	3	1	1	1	1	1	1	1	2
TN	2	2	2	3	3	3	3	4	4	4	3	3	4	4	3	3
TX	3	3	2	2	2	2	2	3	3	3	3	3	3	3	3	3
UT	2	2	3	3	2	1	1	1	1	1	1	1	1	1	1	1
VT	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
VA	2	1	1	1	1	3	3	3	3	2	2	2	2	2	2	2
WA	2	3	3	3	3	3	4	4	4	4	4	4	3	3	2	3
WV	3	3	3	3	3	2	2	1	1	1	1	1	1	1	1	2
WI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
WY	4	3	3	3	3	3	3	3	4	4	4	4	4	4	4	4

Conclusion

This chapter summarizes the Eviction Lab database, describes the measures of eviction to be used in later empirical work, and discusses the comprehensiveness of the state-level data. I propose an additional, created measure of eviction, the likelihood of eviction. This will be a useful measure in some of the empirical analyses that follow. Additionally, I find that when completing analyses at the state-level, researchers need to adjust for data quality, as some eviction estimates at the state-level better represent the likely number of evictions in their state than others due to the consistency and completeness of their data.

CHAPTER V

THE US EVICTION CRISIS

Since its release, the Eviction Lab database has been cited as evidence of an *eviction crisis*. However, references to this crisis are inconsistent. Some articles suggest a national crisis, pointing to the large number of evictions in 2016 (Brennan, 2018; Capps, 2018; Goldberg, 2018), while others mention a local crisis, citing a specific city's ranking within the Eviction Lab's top evicting cities (Goldberg, 2018; Gergen & Mayer, 2018; Sills et al., 2018). What do we mean when we refer to the US eviction crisis? Because a consistent definition of the US eviction crisis has not been provided, we have little understanding of what constitutes an eviction crisis.

A better understanding of what constitutes an eviction crisis will aid US government officials and private organizations that seek to reduce or prevent evictions. In this chapter, I will use state- and county-level data from the Eviction Lab to study eviction at the national, state, and local level from 2002-2016. By exploring the prevalence of eviction over time and across geographies, I will be able to comment on what constitutes an eviction crisis in the US.

Background

The Efficient Level of Evictions

From economics perspective, we approach this question in terms of efficiency. What is the efficient level of evictions? Despite eviction's potential negative consequences, the efficient level of evictions is not zero. Eviction is the process through which a landlord removes a tenant from the rental property when a tenant fails to maintain some aspect of the lease. Tenants who purposely fail to maintain some aspect of the lease must be evicted, and as long as there are such tenants, the efficient level of evictions is nonzero.

In a simple partial equilibrium setting, the efficient level of evictions is found at the intersection of the marginal social cost and marginal social benefit curves. The marginal social cost is the sum of the marginal private cost and the marginal external cost and represents the change in society's total cost associated an additional eviction, while the marginal social benefit is the sum of the marginal private benefit and the marginal external benefit and represents the change in society's total benefit associated with an additional eviction. Marginal external costs are costs of eviction imposed on parties other than the landlord or tenant, and marginal external benefits are benefits of eviction received by parties other than the landlord or tenant. For simplicity, we will assume there are no marginal external benefits. At the intersection, the marginal social cost of the next eviction is exactly equal to the marginal social benefit of the next eviction.

Evictions result from decisions made by individual landlords. A landlord compares their marginal private costs to their marginal private benefits, and in equilibrium the landlord operates where marginal private benefit is equal to marginal private cost ignoring any external costs. For the landlord, the marginal private costs include court fees, turnover fees, and search costs, while the marginal private benefits include rent from a new, potentially better tenant.

However, a problem arises if there are marginal external costs associated with eviction. These costs may include sidewalk cleanup, enforcement of evictions, homelessness, and increases in individuals requiring aid. Assuming no marginal external benefits for simplicity, the existence of marginal external costs leads the private equilibrium number of evictions to be higher than the socially optimal level of evictions. As a result, society operates at an inefficient level of evictions.

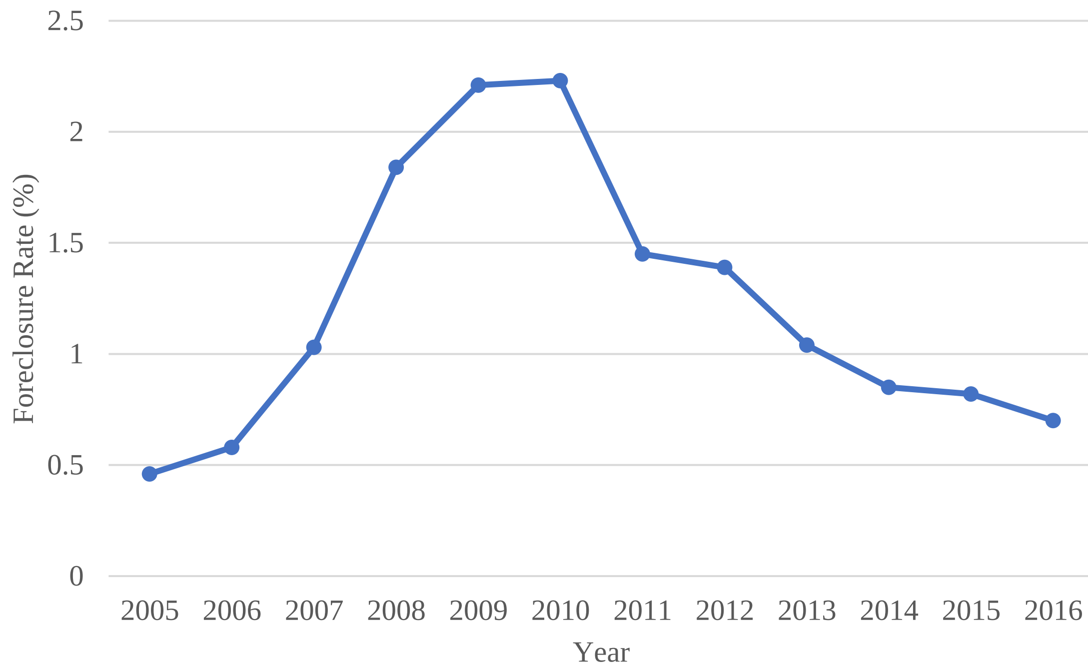
Previous research ties eviction to numerous consequences including homelessness, residential instability, economic hardship, job loss, and physical and mental health issues (Crane & Warner, 2000; Desmond & Kimbro, 2015; Desmond & Shollenberger, 2015; Desmond et al., 2015; Desmond & Gershenson, 2016a; Vasquez-Vera, 2017; Collinson & Reed, 2018; Humphries et al., 2018, Kahlmeter et al., 2018; Rojas & Stenberg, 2018). Some of these consequences are not limited to those who experience eviction directly. For example, Lindsey (2010) suggests that eviction can place direct and indirect fiscal costs on governments, taxpayers, and social-welfare groups as they pay for sidewalk cleanup, enforcement of evictions, homelessness, and increases in individuals requiring aid. If landlords are not considering these costs in their decisions to evict, then we are currently operating at an inefficient level of evictions.

The Foreclosure Crisis

There is currently no research to suggest whether we are actually operating at an inefficient level of evictions or not. As a result, we may look to another example of a crisis to compare current levels of evictions to. Because mortgage foreclosures are the homeowner equivalent of evictions, it makes sense to compare the US eviction crisis to the US foreclosure crisis. The *foreclosure crisis* refers to both the spike in mortgage foreclosure rates around the Great Recession and the consistent, historically high mortgage foreclosure rates after the Great Recession (Emmons, 2016).

Figure 5.3 depicts foreclosure filing rates from 2005 to 2016. Although filing rates peaked in 2010, they remained high until 2016. Foreclosure rates above 0.5 percent are historically high. As I explore eviction over time and across geographies, I will be interested in spikes, historically elevated levels, and rates 0.5 percent to constitute an eviction crisis.

Figure 5.1 Foreclosure Filing Rate, 2005-2016



Data

To examine national, state, and local trends in eviction over time, I use state- and county-level data from the Eviction Lab. Specifically, I use eviction filing rates and eviction judgment rates from 2002-2016. I also construct my measure, the likelihood of eviction, from 2002-2016. Recall that this variable captures the likelihood that an eviction filing results in an eviction judgment.

At the national-level, I examine trends in eviction over time using data from all states except Alaska, Hawaii, and the District of Columbia. Excluding these states addresses data issues discussed in Chapter IV. At the state- and local-level, I examine trends in eviction over time using data from a selection of "core" states. To be included in the "core" sample, states must satisfy the following criteria:

(1) Eviction data in the state must be high quality, as measured by my data quality variable

(2) Eviction data in the state must include both eviction filings and eviction judgments

Table 5.1 depicts where each state falls in terms of data quality and inclusion of eviction filings and eviction judgments. The states located in row 1, column 1 are in the "core" sample. Seventeen states are included.

Table 5.1.
States in Sample

Quality	Contains filings and judgments	Missing filings	Missing judgments
High	AL, DE, FL, IA, IL, KS, ME, MI, MO, NE, NC, OH, OK, OR, PA, UT, WI		AR, ND
Medium	GA, ID, IN, MA, MN, MS, NV, NJ, NM, VA, WV	RI, SC, SD	RI, SC, SD
Low	AZ, CA, CO, CT, KY, LA, MD, NY, TN, TX, VT, WA, WY	NH	NH

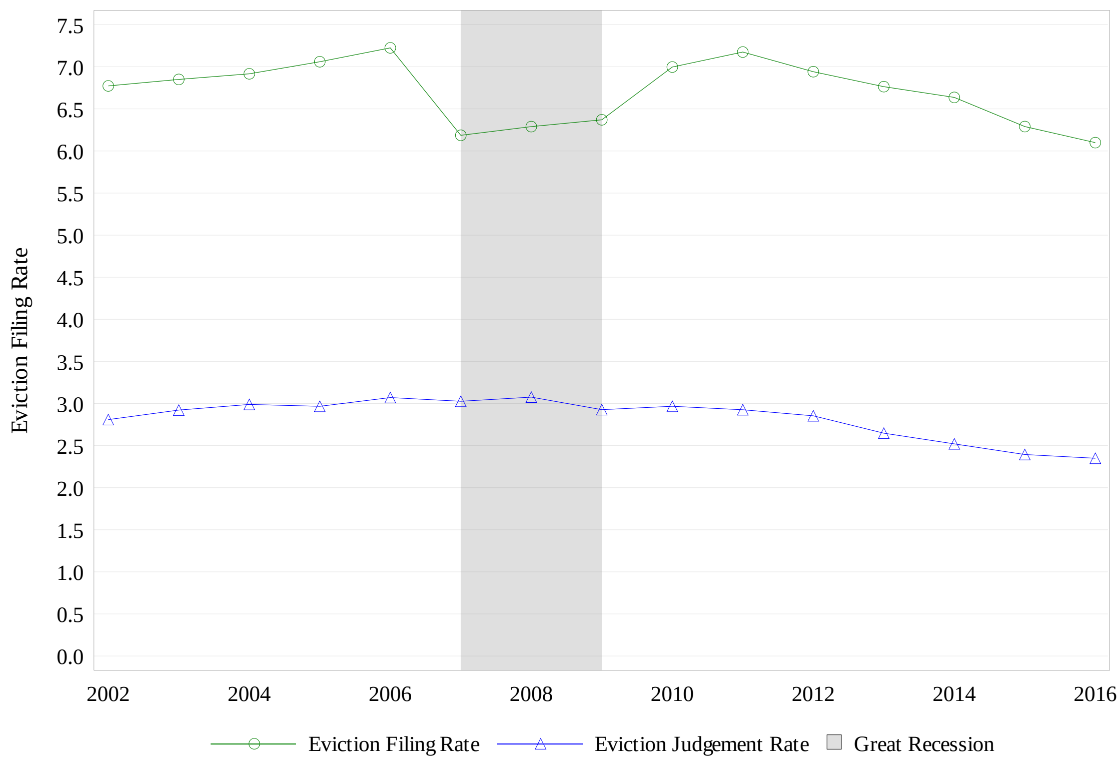
Notes: If a state is missing filings and/or missing judgments in at least one year from 2002-2016, it is placed in column 2 and/or column 3. A state needs to contain both eviction filings and eviction judgments for all years from 2002-2016 for it to appear in column 1.

Eviction at the National Level

I begin by exploring national trends in eviction over time. Figure 5.2 depicts the US eviction filing rate and the US eviction judgment rate from 2002 to 2016. The filing rate is the number of eviction filings per 100 renter-occupied households, while the judgment rate is the number of eviction judgments per 100 renter-occupied households. From 2002-2016, the filing rate remains above the judgment rate. The filing rate sees a drop from 2007-2009, while the judgment rate remains relatively flat over time. Both the filing rate and the judgment rate have decreased slightly from 2002. The filing rate has decreased from 6.77 eviction filings per 100 renter-occupied households in 2002 to 6.10 in 2016, while the judgment rate has decreased from 2.81 eviction judgments per 100 renter-occupied households in 2002 to 2.35 in 2016.

We can compare Figure 5.2 to the foreclosure crisis to get a sense of whether it represents an eviction crisis. Neither the eviction filing rate or the eviction judgment rate spike during 2002-2016. Although the filing rate does gradually increase starting in 2009, it follows a sharp decrease from 2007-2009. Because we do not have data further back, it is impossible to tell if these graphs represent a sustained historically elevated level of evictions. What we can say is that both the eviction filing rate and the eviction judgment rate are well above the foreclosure rate over this time period, even when foreclosure rates are considered to be at crisis levels. As a result, if we use the foreclosure crisis as a comparable measure for the US eviction crisis, then these graphs certainly do suggest a persistent eviction crisis over the last fifteen.

Figure 5.2 Eviction Filing Rate and Eviction Judgment Rate, 2002-2016



Note: Excludes Alaska, Hawaii, and DC.

Eviction at the State Level

The national trends provide insight, but they mask what is happening at the state level. It is possible that some state trends look very different from the national trends. As a result, I explore state trends in eviction over time. I restrict my analysis to my 17 "core" states. Figure 5.3 depicts the eviction filing rate and the eviction judgment rate from 2002 to 2016 for each of my core states. For all states, from 2002-2016, the filing rate remains above the judgment rate. However, there is a lot of variation in how much different the eviction filing rate is from the eviction judgment rate. For example, the filing rate in Maine is only slightly above the judgement rate, but in Michigan and North Carolina the two rates are much further apart.

Twelve (Alabama, Florida, Illinois, Iowa, Kansas, Maine, Missouri, Nebraska, Ohio, Oregon, Utah, and Wisconsin) of the seventeen states do not have much movement in their eviction filing rates or eviction judgement rates. Florida and Oregon have slight downward trends in both their filing rates and judgement rates. Maine has a slight upward trend in both of its rates. The other eight states remain relatively flat over time.

The remaining five states (Delaware, Michigan, North Carolina, Oklahoma, and Pennsylvania) have much more movement in their eviction filing rates or eviction judgement rates (or both). Delaware's eviction filing rate nearly doubles in 2009, while its eviction judgement rate trends downward over time. Michigan's rates follow a clear arc, while North Carolina's rates look to be converging over time. Oklahoma sees a spike in both its eviction filing rate and its eviction judgement rate in 2012. Finally, Pennsylvania's eviction filing rate starts to dip in 2014, while its eviction judgement rate spikes in 2006. There is no consistent trend in these five states, nor is there a consistent trend across the entire core.

Again, we can compare Figure 5.3 to the foreclosure crisis to determine the extent of an eviction crisis at the state level. A few states do see spikes in their filing rates, judgment rates, or both during 2002-2016. These spikes may suggest a crisis. For states that have relatively flat filing rates and judgment rates over time, we again do not have data further back, so it is impossible to tell if these graphs represent a sustained historically elevated level of evictions. However, we can say that both the eviction filing rate and the eviction judgment rate for most states are well above the foreclosure rate over this time period, even when it was considered to be at crisis levels. As a result, if we again use the foreclosure crisis as a measure of the eviction crisis, then these graphs certainly do suggest a persistent eviction crisis over the last fifteen or so years.

Figure 5.3 Eviction Filing Rate and Eviction Judgment Rate, 2002-2016

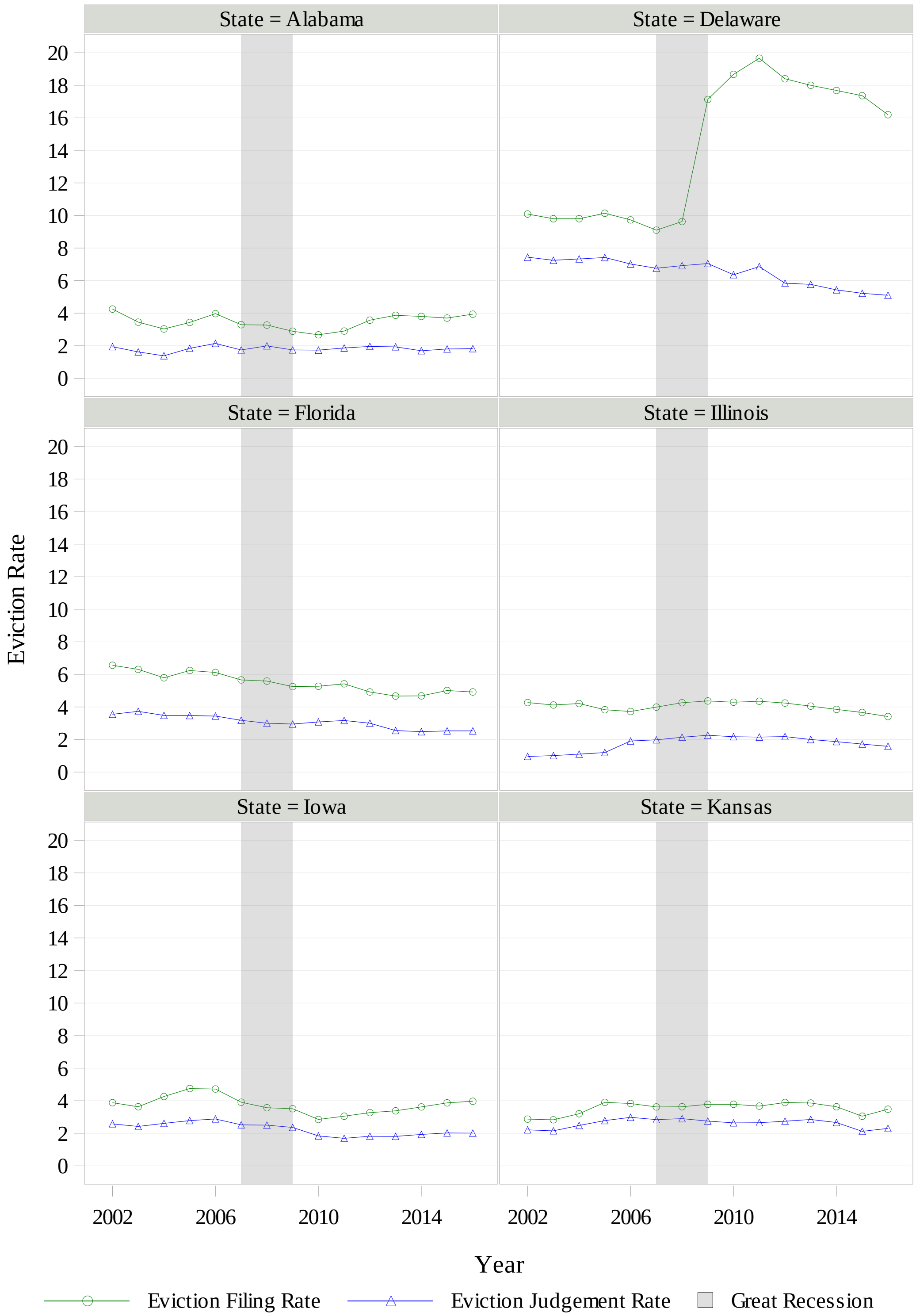


Figure 5.3 Eviction Filing Rate and Eviction Judgment Rate, 2002-2016

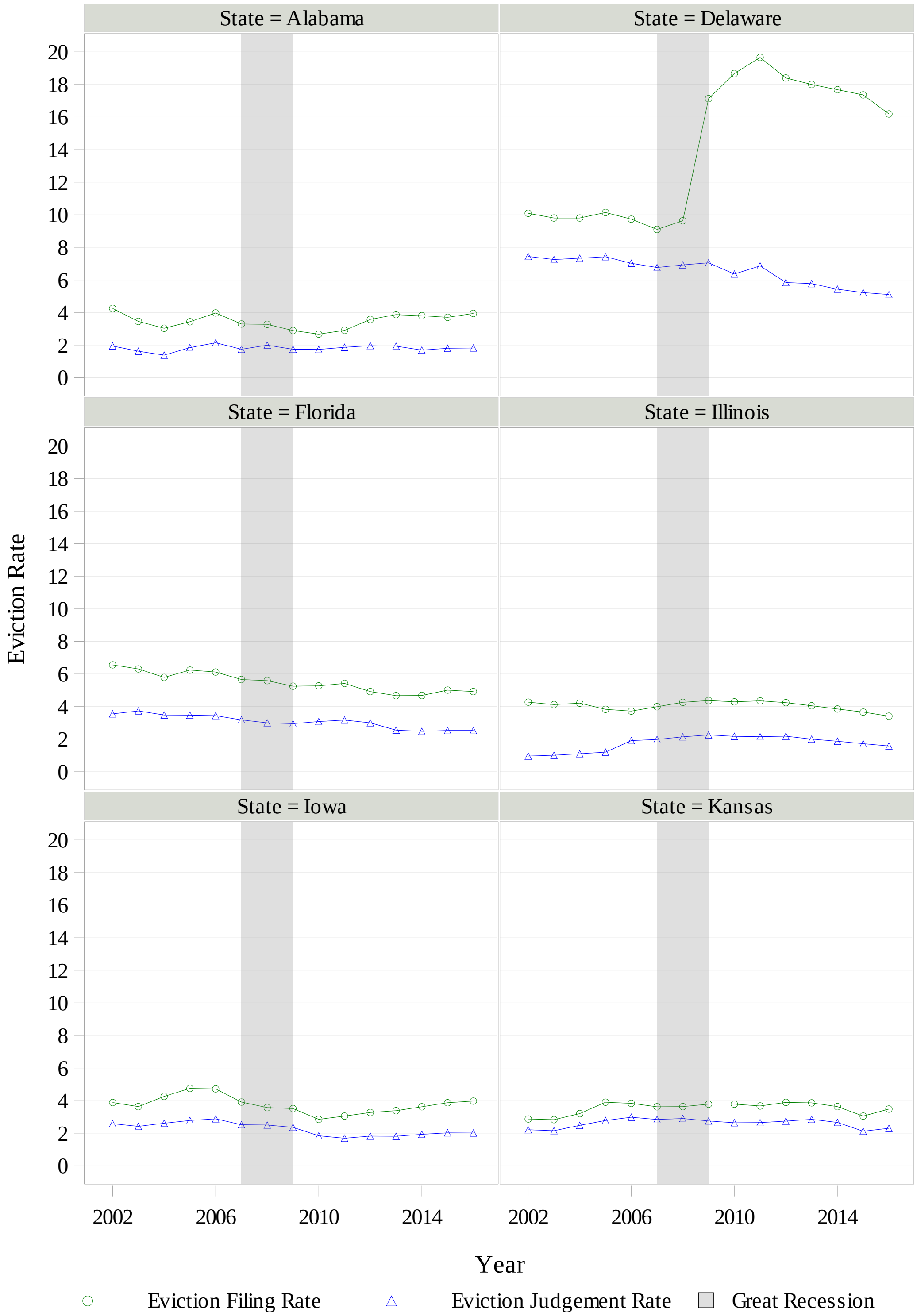


Figure 5.3 Eviction Filing Rate and Eviction Judgment Rate, 2002-2016

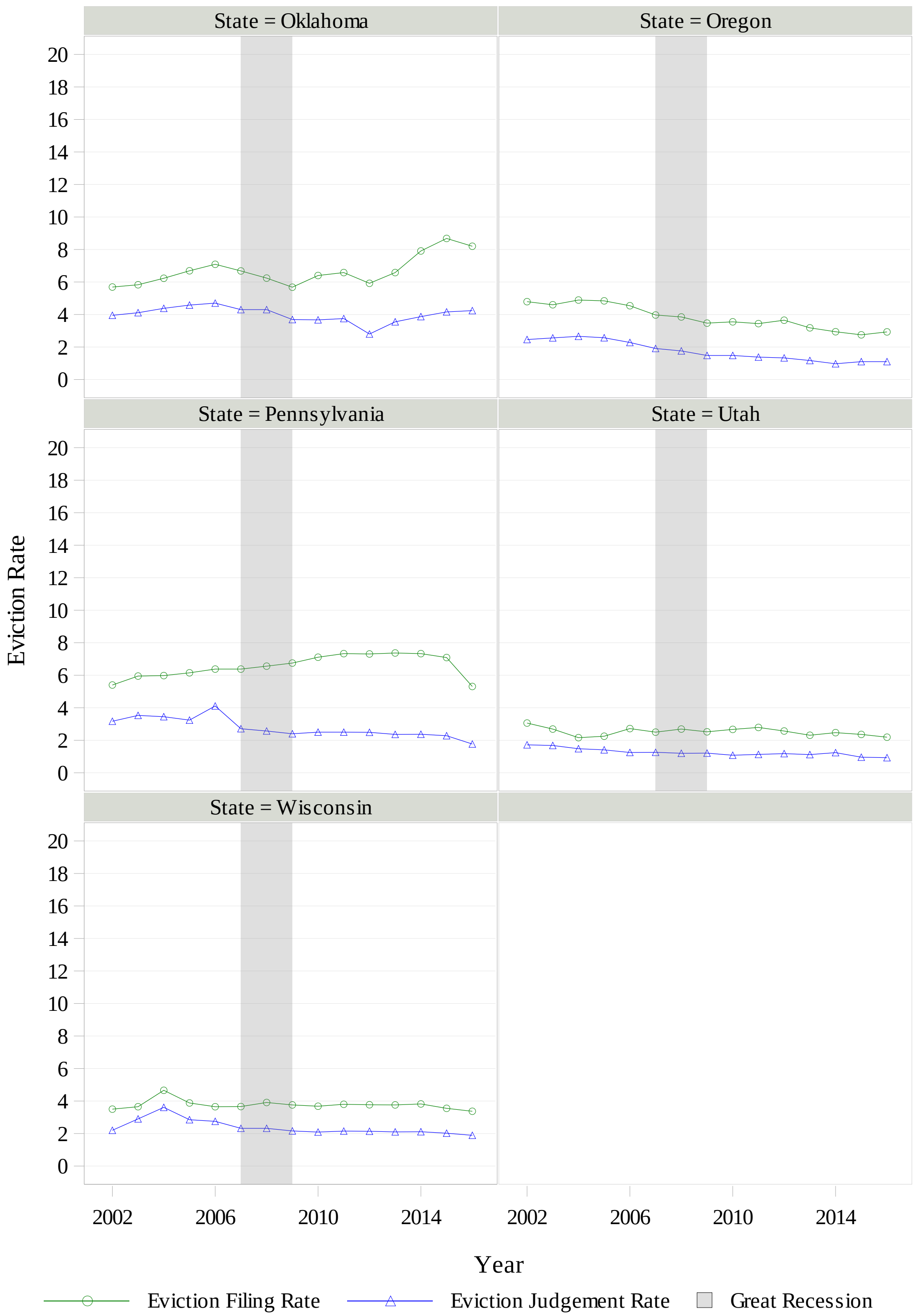


Figure 5.4 depicts the likelihood of eviction from 2002 to 2016 for my core states. The likelihood of eviction is much more volatile than the eviction filing rate and the eviction judgment rate. Despite the volatility, five states (Alabama, Florida, Maine, Missouri, and Ohio) have no clear trend over time. Of the remaining twelve states, nine (Delaware, Iowa, Kansas, Michigan, Oklahoma, Oregon, Pennsylvania, Utah, and Wisconsin) have a clear downward trend in their likelihood of eviction. That is, renters in these states are less likely to receive an eviction judgement if they received an eviction filing than they were in 2002. The remaining three states (Illinois, Nebraska, and North Carolina) have a clear upward trend. Renters in these states are more likely to receive an eviction judgment if they received an eviction filing in 2016 than they were in 2002. As with the filing rate and judgment rate, there is no consistent trend across the entire core.

Figure 5.4 Likelihood of Eviction, 2002-2016

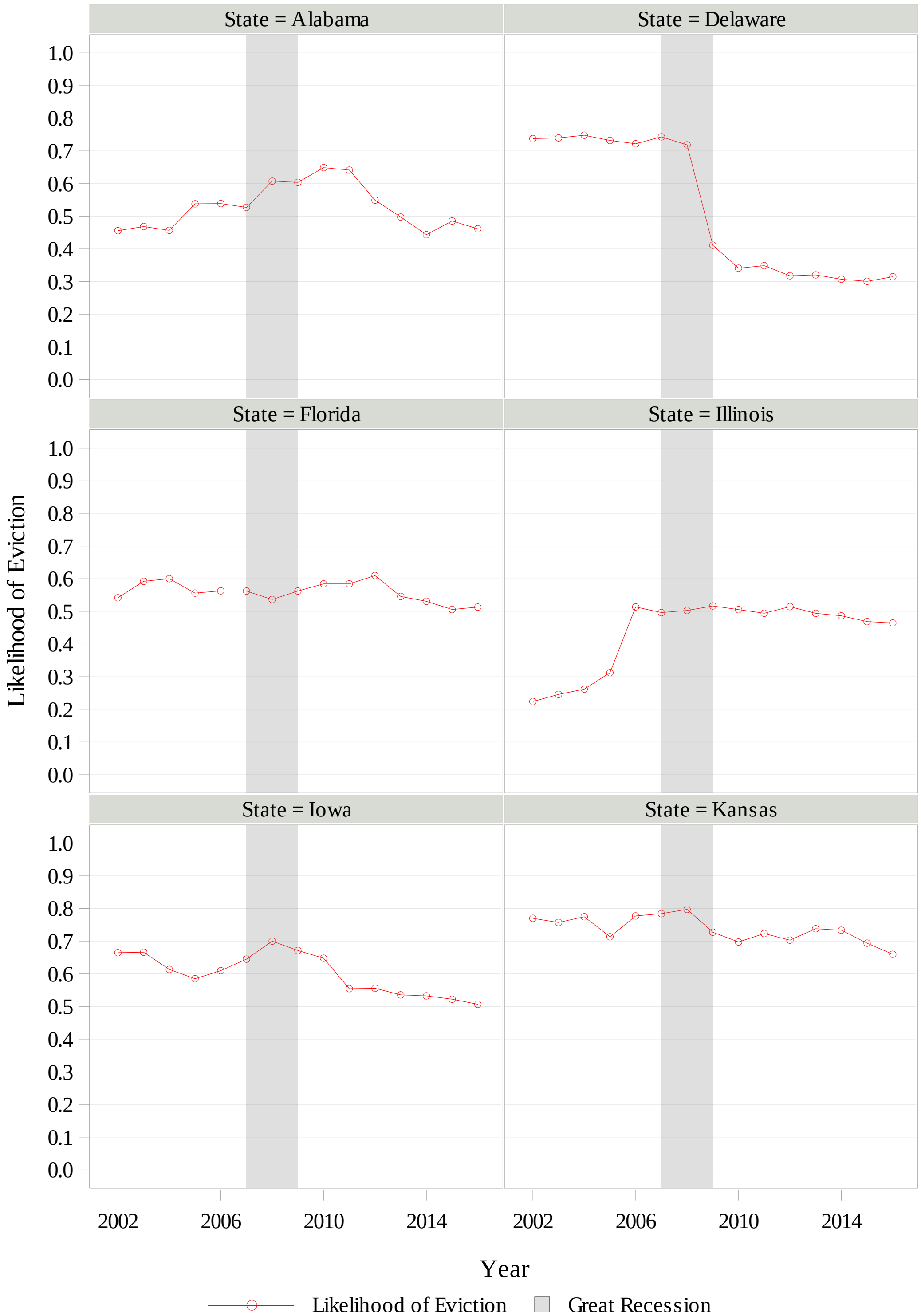


Figure 5.4 Likelihood of Eviction, 2002-2016

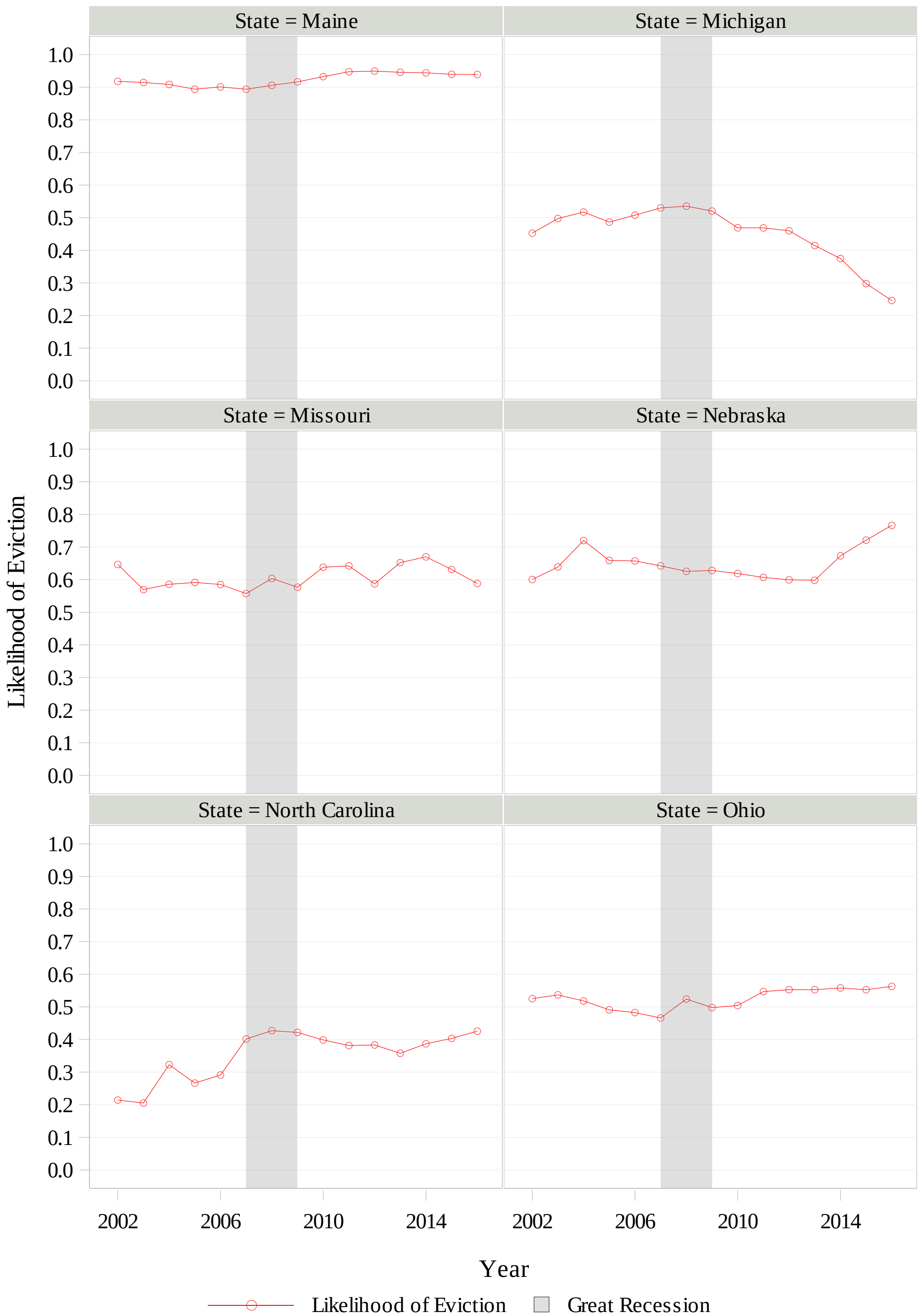
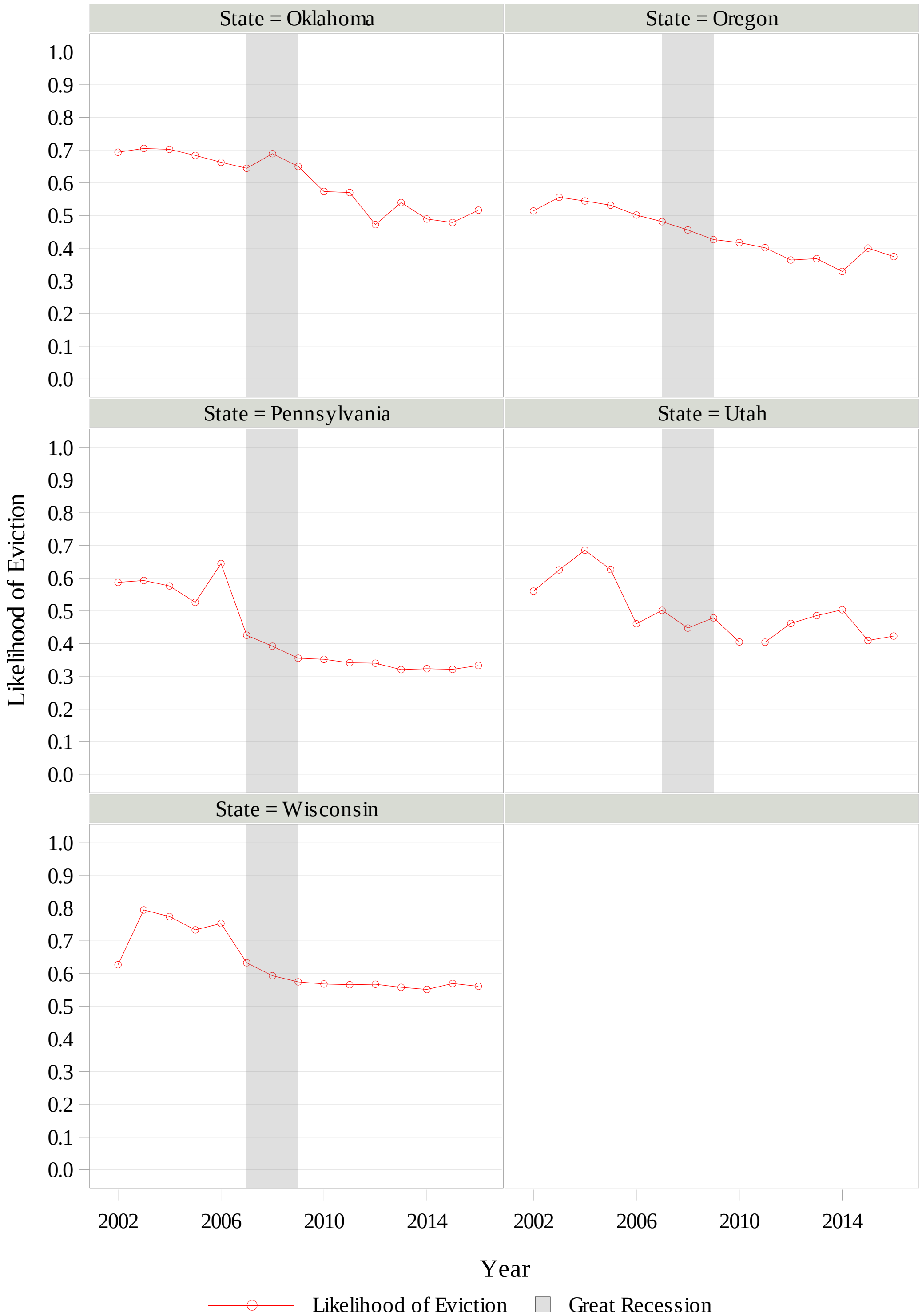


Figure 5.4 Likelihood of Eviction, 2002-2016



Eviction at the County Level

The state trends provide insight, but they mask what is happening at the county level. It is possible that some county trends look very different from the state trends. As a result, I explore county trends in eviction over time. I again restrict my analysis to my 17 “core” states. Figure 5.5 depicts the eviction filing rate from 2002 to 2016 for each state, as well as each county in the state for all of my core states. Including both the counties’ filing rates, as well as the state’s filing rate on the same graphs gives us a better sense of how the county and state level rates relate to one another. Figure 5.5 showcases how the county filing rates can be very different from the state filing rates. A cluster of lines appears in every state’s graphs; however, there is also a bit of range in the filing rates across the counties. Further, all states have counties with filing rates that are incredibly volatile. We did not see this level of volatility in the state-level data.

Beyond the volatility of some counties’ eviction filing rates, two trends emerge: state eviction filing rates that mirror the majority of their counties’ rate and state eviction filing rate that mirror only some of their counties. Delaware and Maine have county-level filing rates that are nearly identical to the state’s eviction filing rate. The state line falls in the middle of the counties. For the other 15 states in the core, the state eviction filing rate appears to be getting pulled away from the majority of the counties’ rates.

Figure 5.5 Eviction Filing Rate, 2002-2016

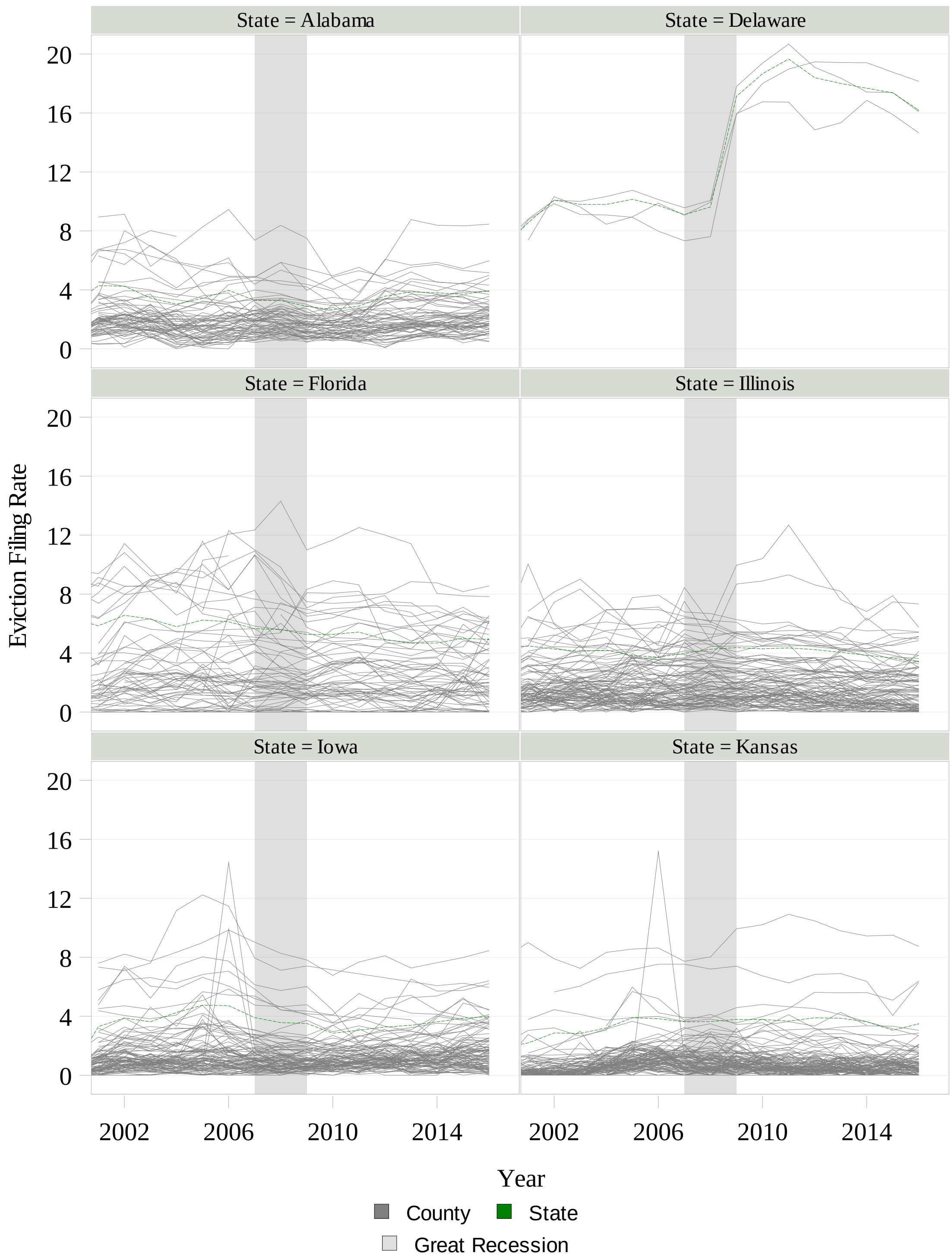


Figure 5.5 Eviction Filing Rate, 2002-2016

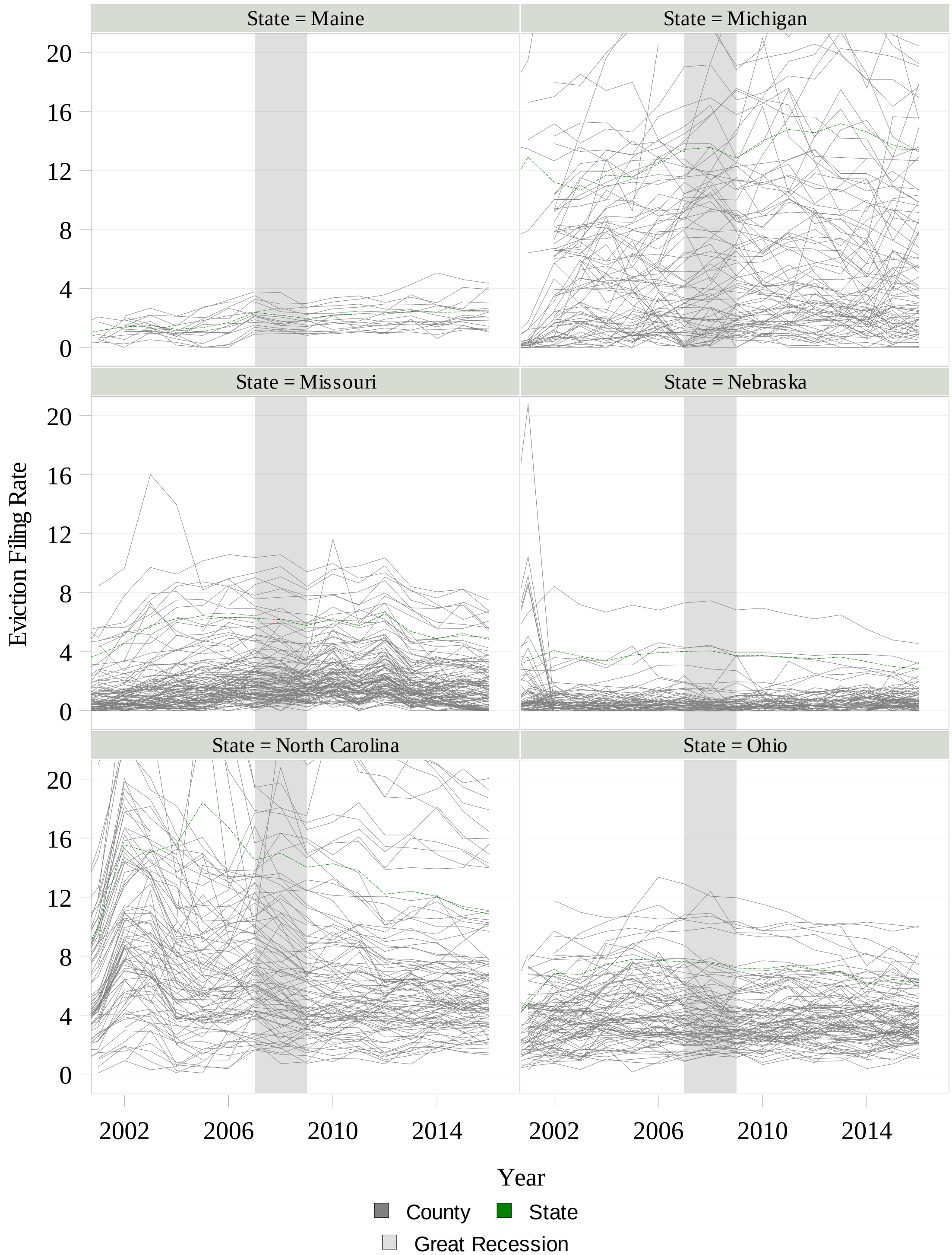


Figure 5.5 Eviction Filing Rate, 2002-2016

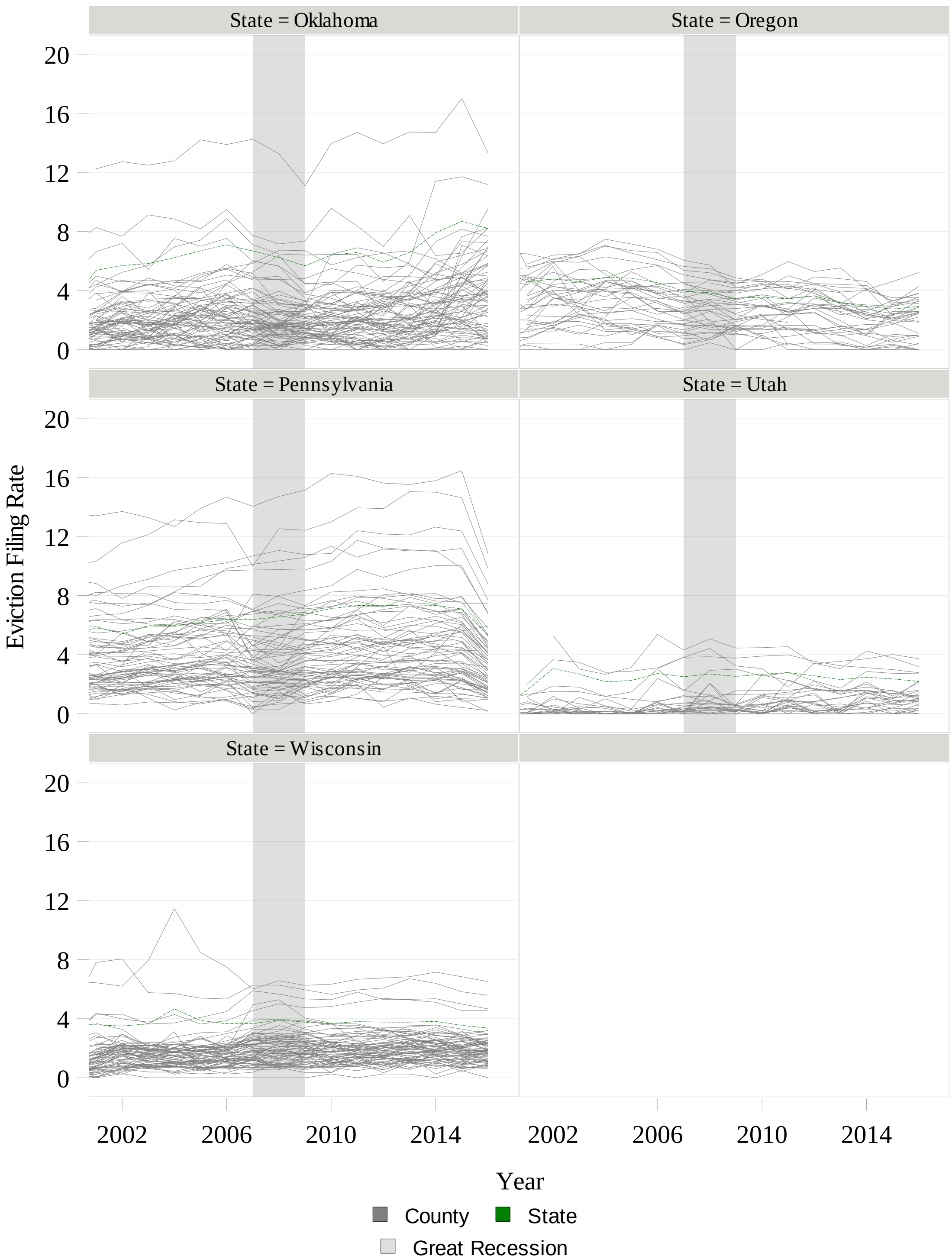


Figure 5.6 depicts the eviction judgment rate from 2002 to 2016 for each state, as well as each county in the state for all of my core states. Including both the county's judgment rates, as well as the state's judgment rate on the same graphs gives us a better sense of how the county and state level rates relate to one another. Figure 5.6 showcases how the county judgment rates can be very different from the state judgment rate. As with the eviction filing rates, there is always a cluster of lines in each state's graphs. However, unlike the eviction filing rates, the eviction judgment rates have much less spread. Although we can see some volatility in the judgment rates, it is not nearly as volatile as the eviction filing rates. The highest eviction judgment rates are lower than the corresponding eviction filing rates.

Figure 5.6 presents two distinct patterns: states that follow the majority of their counties' trends and those that only follow a few counties' trends. There are more states that fall in the middle of their county data than before. These states are Delaware, Illinois, Maine, Michigan, Ohio, Oregon, and Pennsylvania. The other ten states tend to sit more towards the top of the eviction rate cluster, which suggests that there is a county or two that is pulling the state's line away from the cluster.

Figure 5.6 Eviction Judgment Rate, 2002-2016

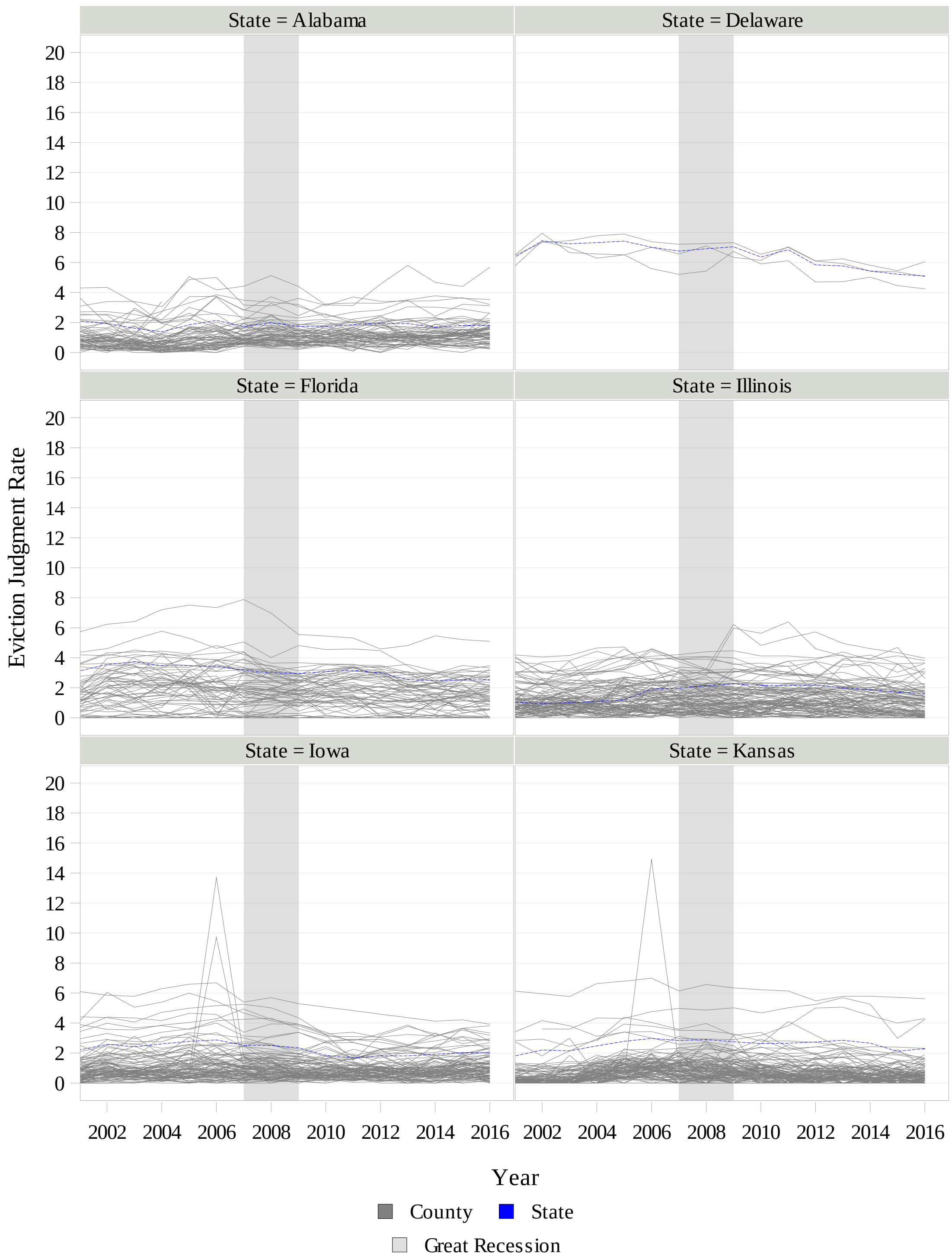


Figure 5.6 Eviction Judgment Rate, 2002-2016

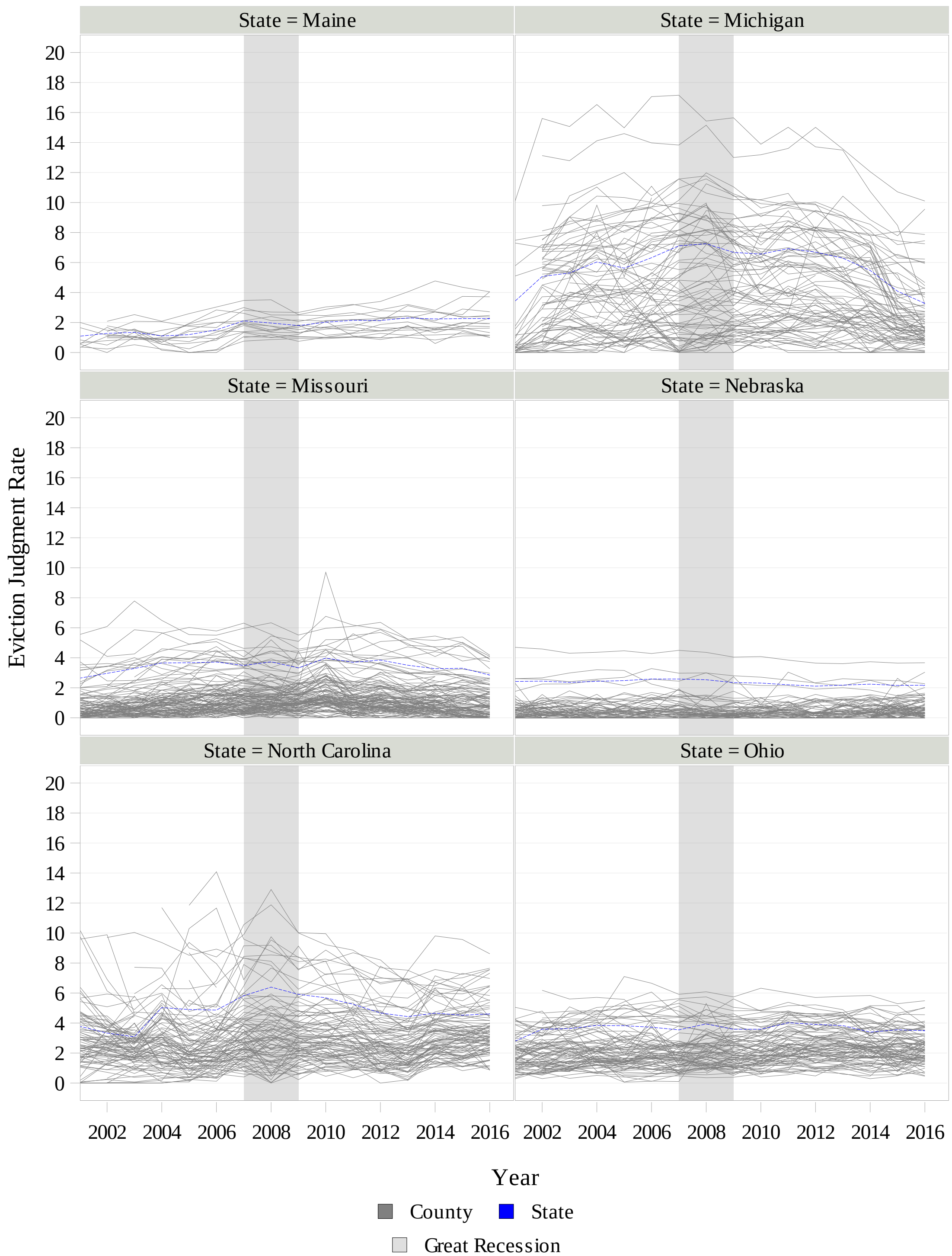
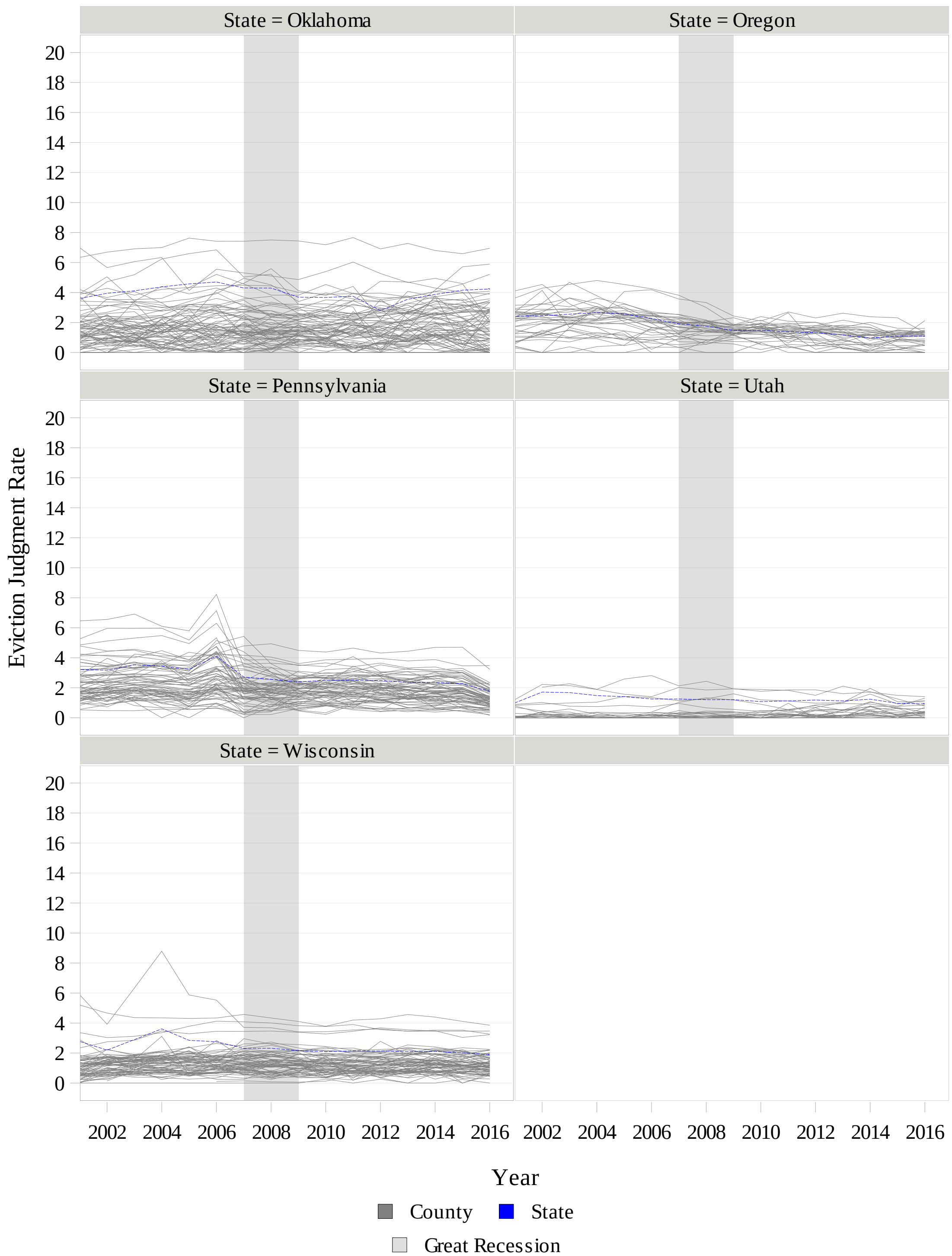


Figure 5.6 Eviction Judgment Rate, 2002-2016



Finally, Figure 5.7 depicts the likelihood of eviction from 2002 to 2016 for over time for counties within the states in our core sample. The state's likelihood of eviction is plotted for comparison. These graphs are the most volatile of all. Most states have counties that bounce between 0 and 1. Although there tend to be clusters, the clusters do not always follow the same trend. For example, Illinois has a lot of counties in the top half of the graph, but there is no clear pattern to their likelihood of eviction. Wisconsin has a distinct trend across numerous counties.

Figure 5.7 Likelihood of Eviction, 2002-2016

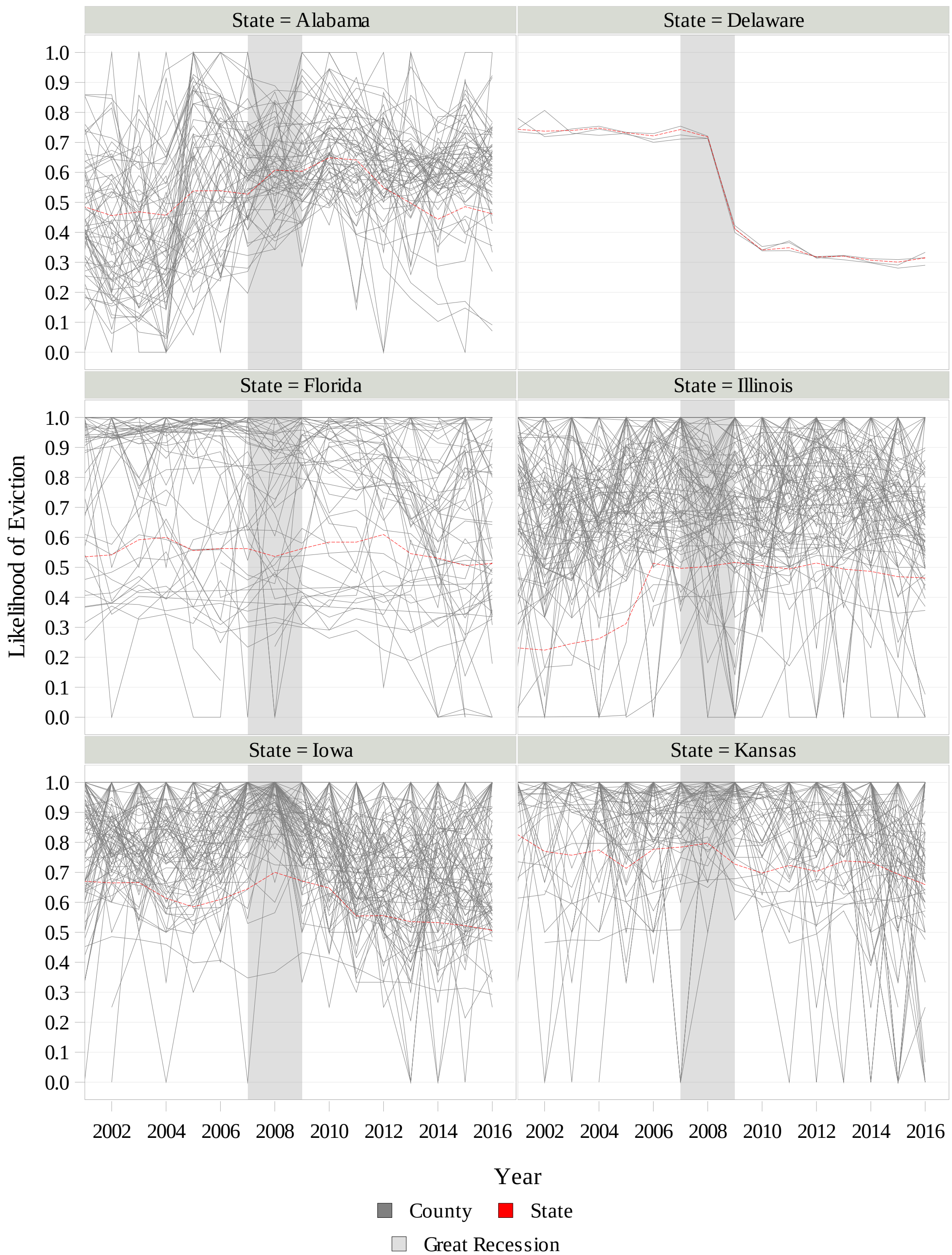


Figure 5.7 Likelihood of Eviction, 2002-2016

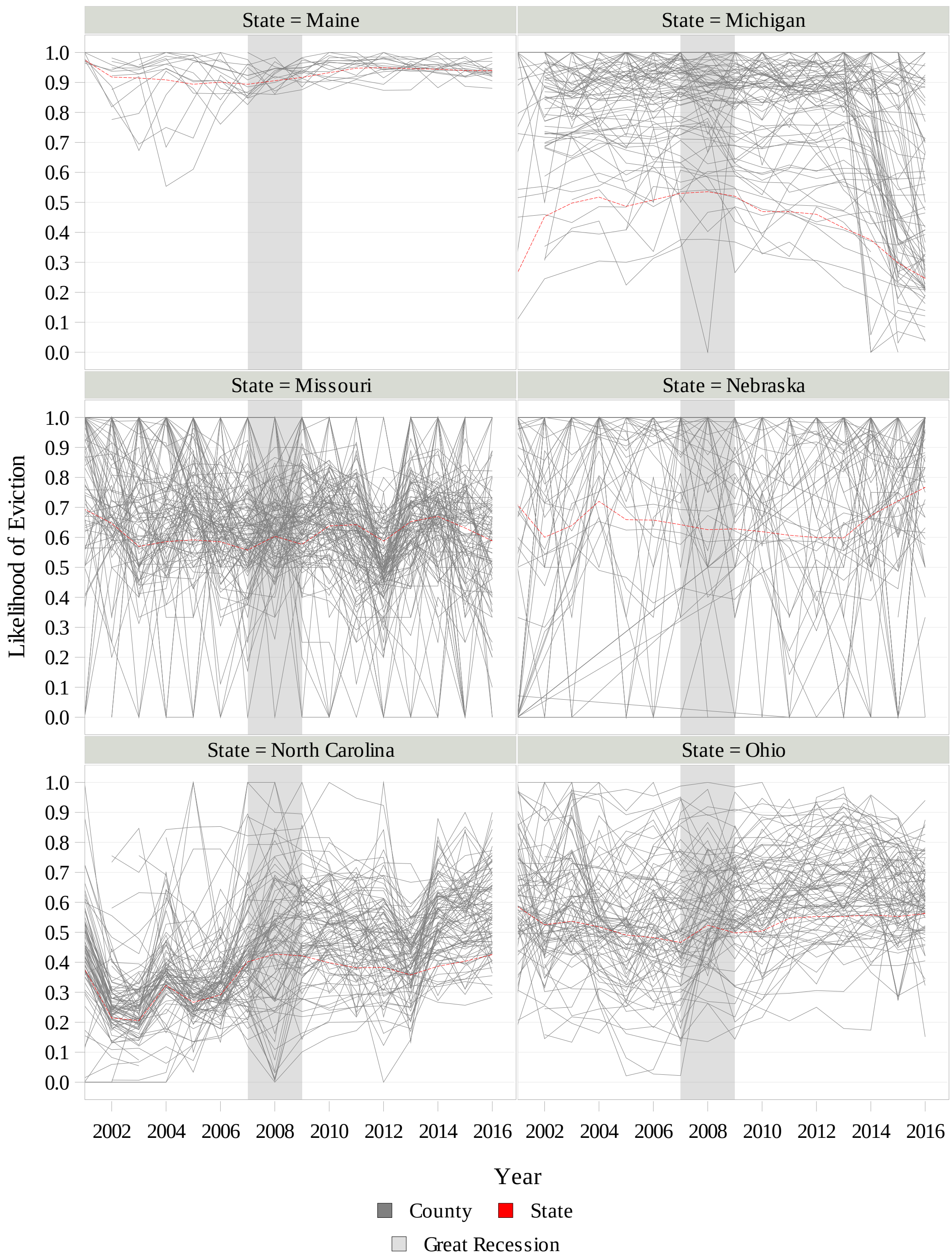
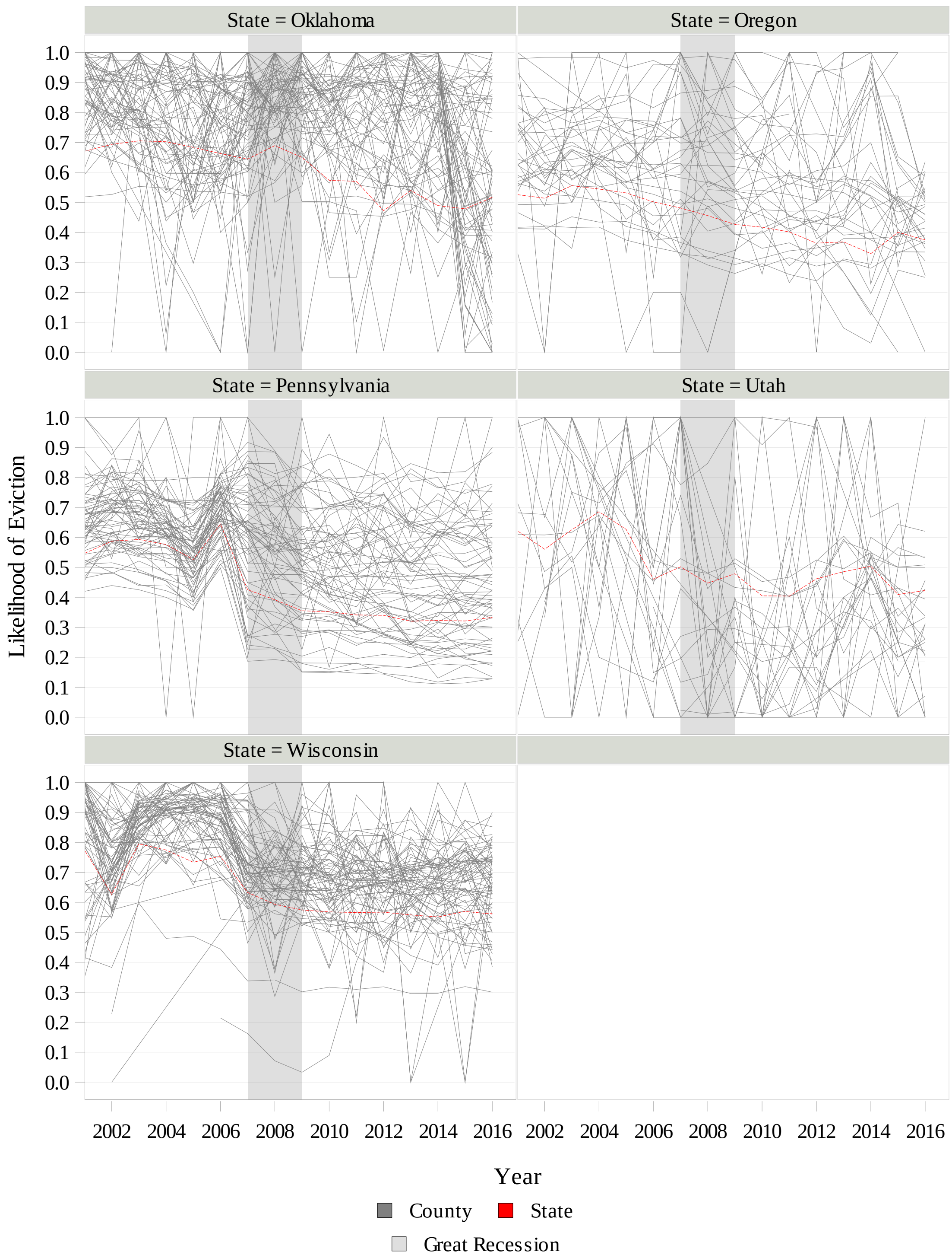


Figure 5.7 Likelihood of Eviction, 2002-2016



These graphs confirm that there is a lot of variation in eviction filing rates, judgement rates, and the likelihood of eviction across areas and over time. A close look at the filing rates and judgement rates suggests that although there are spikes over time, there have not been many spikes that have maintained the higher levels, especially not recently. The likelihood of eviction is incredibly volatile, but that is only capturing the chances of someone receiving a judgment after being filed upon.

Conclusion

There has been much discussion about the US *eviction crisis*. However, we have never defined what constitutes an eviction crisis. From an economics perspective, we may think in terms of the efficient level of evictions. Yet, there is currently no literature to suggest whether we are operating at an inefficient level of evictions or not. As a result, we may look to a different example of a crisis to compare current levels of eviction to. Because foreclosures are the homeowner equivalent of evictions, I compare the US eviction crisis to the foreclosure crisis.

The foreclosure crisis is defined as both the spike in foreclosure rates around the Great Recession and the consistent, historically elevated foreclosure rates after the Great Recession. These historically elevated rates are above 0.5 percent. Using the foreclosure crisis definition as context for the US eviction crisis, my results suggest that the US eviction crisis is a national, state, and local issue.

At the national level, the US eviction crisis is not marked by a spike or a historically elevated level of evictions, but instead by eviction filing rates and eviction judgment rate well above those of the foreclosure rates during the same time period. At the state and local level, the US eviction crisis can be marked by spikes in filing rates, judgment rates, and the likelihood of eviction, as well historically elevated filing rates, judgement rates, and the likelihood of eviction.

Additionally, many states and counties have eviction filing rates and judgment rates well above 0.5 percent.

The goal of this chapter is to provide a first step in understanding what has been deemed the US *eviction crisis*. It is important to understand the crisis, before trying to solve it, because a clear understanding of the problem helps us to create the most effective solutions. It is impossible to solve a problem that you do not understand.

CHAPTER VI

THE VARIATION IN EVICTION RATES ACROSS US COUNTIES

Chapter V highlighted a large variation in eviction rates across US counties, yet we do not know why this variation exists. As discussed in Chapter II, the prior literature offers explanations for why some individuals are evicted, while seemingly similar individuals are not. The results suggest that both demographic factors, such as race, ethnicity, and family structure and economic factors, such as rent, income, and poverty, contribute to differences in eviction outcomes. Demographic factors have been of particular interest because of the possibility of discrimination. However, the previous research is limited by data availability. Most conclusions have been reached using data from one city or county. Further, nearly all the research has focused on urban areas. As a result, we do not know if results from the literature generalize across the US.

The Eviction Lab provides an opportunity to study differences in eviction rates across US counties. This chapter uses county-level data from the Eviction Lab to determine which factors are associated with differences in eviction rates across the US. Specifically, it seeks to determine in the relationship between county-level eviction rates on the one hand and county-level demographic characteristics and economic conditions on the other. In doing so, it explores and expands previous explanations provided by the literature.

Ultimately, distinguishing which, if any, explanations contribute to geographic disparities in eviction rates is an essential step toward developing place-level targeted interventions. If county-level characteristics that predict differences are economic, then solutions like affordable housing should be the focus; however, if county-level characteristics that predict differences are demographic, then these solutions may not be enough.

Data

Outcomes

My dependent variables of interest are the county-level eviction filing rate and the county-level eviction judgment rate. Both of these variables are contained in the Eviction Lab. Recall that the eviction filing rate is the number of eviction filings, including multiple against the same household, per the number of renter-occupied households. The eviction judgment rate is the number of eviction judgments per the number of renter-occupied households. As rates, both the eviction filing rate and the eviction judgment rate fall between zero and one[4]. I use data from 2005-2016, because my covariates are only available during that time period.

Covariates

County-level explanatory variables were selected based on the literature, specifically focusing on demographic and economic characteristics. Following the literature, I select the following demographic controls: race, ethnicity, and female headed household status. I also include a measure of racial residential segregation, which has not previously been included in eviction research, and educational attainment, which has been used as a control in some of prior the literature.

Because I am using county rather than individual level data, many of these variables will be the percentage of individuals or households having a certain characteristic. Race is captured by the percentage of black residents in a county. Ethnicity is captured by the percentage of Hispanic (of any race) residents in the county. Racial residential segregation is measured by the black-white dissimilarity index. The dissimilarity index measures the degree of segregation between two groups by looking at their relative distributions across a smaller geographical area within a

[4] The eviction filing rate could be greater than one, but in my data, I do not have any observations greater than one. As a result, I ignore this characteristic of the data in this analysis.

larger geographical area. Here, the dissimilarity index captures the relative distribution across census tracts within the same county. The index usually runs from 0 (complete integration) to 1 (complete segregation). Female headed households are captured by the percentage of families in the county with a female head, no husband present, and their own children. Finally, educational attainment is captured for the county population age 25 and over. I separate educational attainment into the following five groups: less than a high school education, a high school degree, some college, a college degree, and more than a college degree.

To account for economic conditions, I include variables measuring rent, income, poverty, and unemployment in my analysis. Rent is captured by real median gross rent. Income is captured by real median household income. Both rent and income are measured in 2016 dollars. Poverty is measured by the percentage of families in a county with income below the poverty line. Finally, unemployment is captured by the county's unemployment rate.

Lastly, in the analysis of all counties, I include a geographic control for whether a county is considered urban or not. I define urban by the Census bureau definition of a population 50,000 or more

Data for covariates come from the American Community Survey (ACS) and the Bureau of Labor Statistics Local Area Unemployment Statistics (BLS LAUS). The ACS provides the most up to date data on population and housing characteristics, while the BLS LAUS provides the most up to date data on unemployment. To study all counties across the US, I use the ACS 5-year estimates for all covariates except unemployment. The ACS 5-year estimates are essentially a 5-year average of data from each county. As a result, I must use the same estimate for multiple years. I used the 2009 ACS 5-year estimates for 2005-2009, the 2012 ACS 5-year estimates for 2010 and the 2015 ACS 5-year estimates for 2011-2016. For unemployment, I use county-level unemployment data from BLS LAUS for 2005-2016. These are yearly estimates.

Samples

I begin by eliminating all counties from Alaska, Hawaii, DC, and Maryland to address data quality issues from Chapter IV. I also eliminate any counties with missing data for any of the outcome and control variables. As a result, the full sample contains 28,306 county-year observations across 2005-2016. The sample represents 2,662 of the 3,242 unique counties or county equivalents in the US. Because counties that do not consistently show up in the data may be different from those that do, I perform a sensitivity analysis using a balanced panel. I also construct an urban sample to understand if the factors that affect the differences in the eviction rates across the entire US differ from those that affect differences in eviction rates across urban counties. The urban sample, which eliminates counties in the same way as the full sample, contains 8,910 county-year observations across 2005-2016. This panel is also unbalanced.

Table 6.1 presents summary statistics for both the full and urban sample. The full sample provides an understanding of the demographics and economics of all counties across the US, while the urban sample provides a narrower view. There are differences in the means across the two samples. In the full sample, the eviction filing rate and the eviction judgement rate are lower than in the urban sample. These results suggest that eviction is more prevalent in urban counties. Additionally, the full sample of counties is less segregated than the urban sample. Across the full sample, the dissimilarity index is 0.41, while across the urban sample, the dissimilarity index is 0.47. The full sample has slightly lower levels of female-headed households. The urban sample is more highly educated. The full sample has lower median household income and median gross rents, as well as median rent burden. However, the full sample has higher levels of poverty. The average unemployment rate between the two samples is similar.

Table 6.1
Summary Statistics

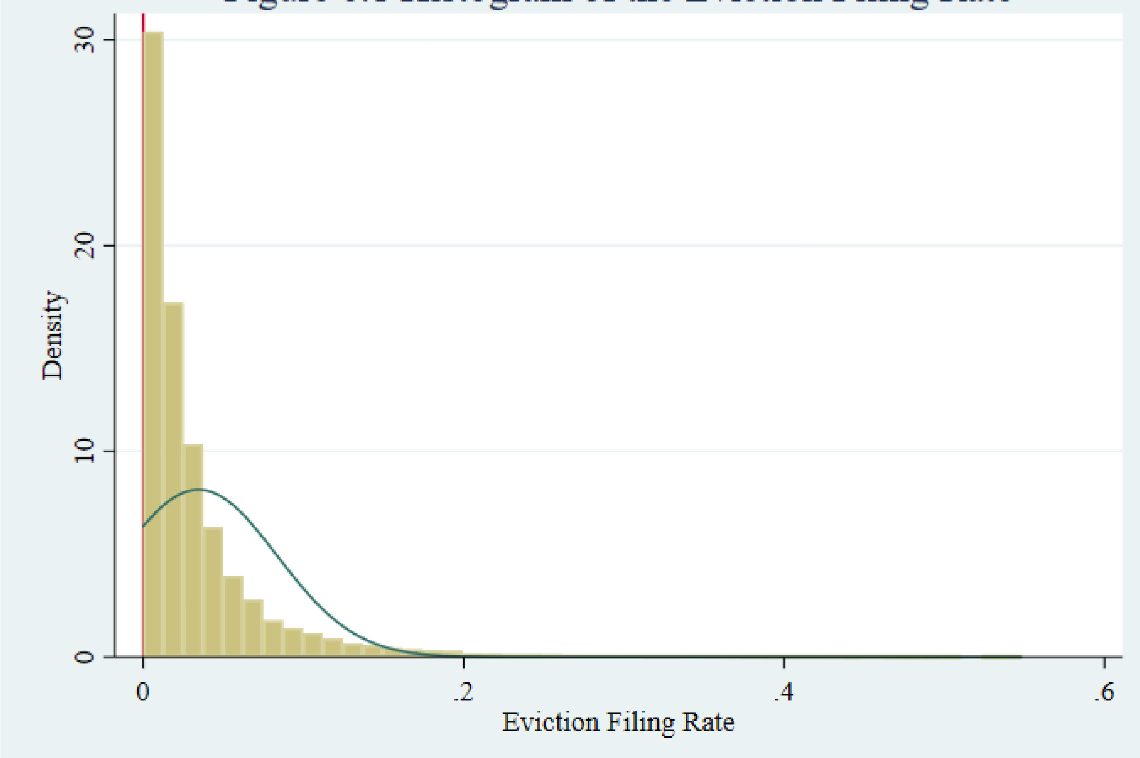
	Full Sample				Urban Sample			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Eviction Filing Rate	0.03	0.05	0.00	0.55	0.06	0.07	0.00	0.55
Eviction Judgment Rate	0.02	0.02	0.00	0.24	0.03	0.02	0.00	0.24
% Black	9.02	14.36	0.01	86.76	10.27	11.87	0.06	70.94
% Hispanic	8.30	13.11	0.00	95.54	9.56	12.07	0.50	95.54
Dissimilarity Index	0.41	0.18	0.00	0.99	0.47	0.12	0.11	0.83
% Female-Headed Households	9.54	3.52	0.00	29.60	10.50	3.01	2.87	28.79
% < HS Grad	16.03	7.17	1.26	48.70	13.35	5.51	2.32	46.29
% HS Grad	35.52	6.98	7.52	55.10	31.25	6.87	8.30	52.16
% Some College	29.08	5.30	10.83	48.82	29.85	4.50	12.29	43.83
% College Grad	12.67	5.34	2.50	42.20	16.27	5.61	5.44	37.78
Median Rent (100s)	7.14	1.86	1.99	19.40	8.60	2.00	5.19	18.68
Median Income (1000s)	48.33	12.38	19.58	139.58	55.47	13.84	28.92	137.99
% Families in Poverty	11.87	5.44	0.49	44.32	10.46	4.21	1.43	31.74
Unemployment Rate (%)	6.77	2.96	0.20	26.30	6.63	2.66	0.20	19.00
Urban (%)	0.31	0.46	0.00	1.00	1.00	0.00	1.00	1.00
Observations	28,306				8,910			

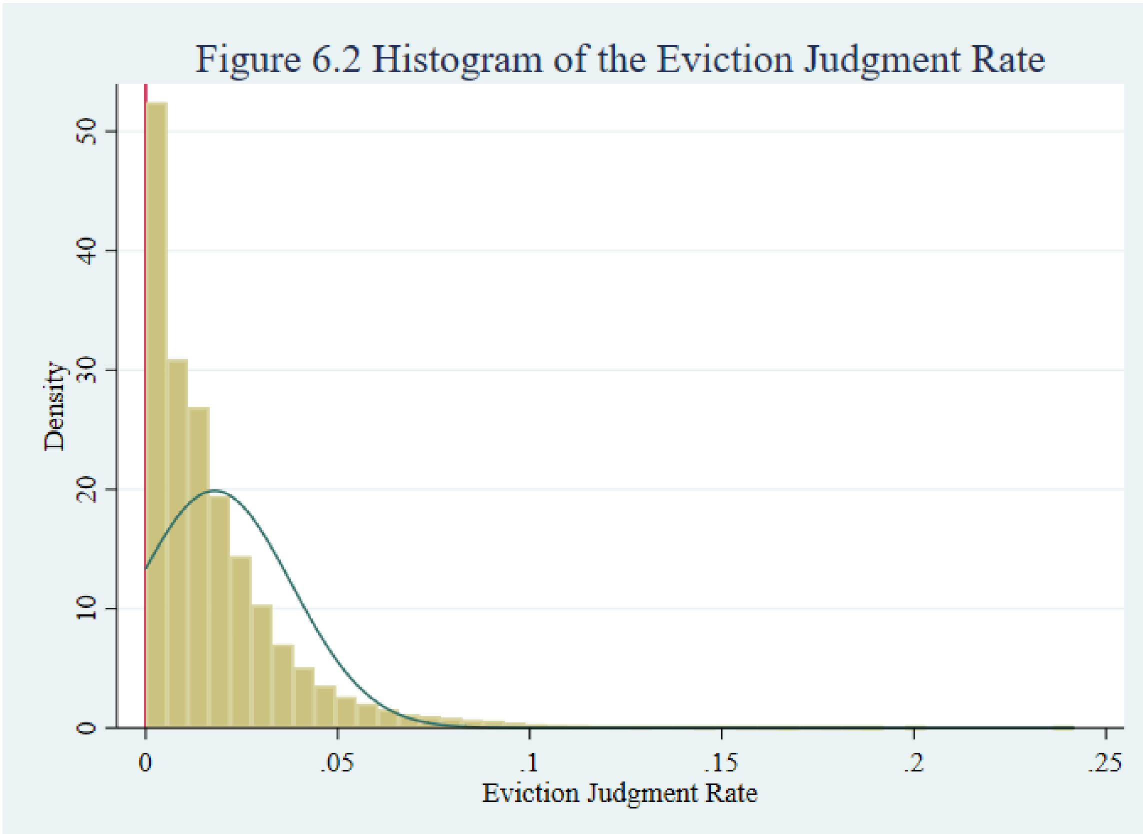
The differences in the summary statistics are worth noting as they suggest that we may see different outcomes in the regression models that follow. Also, given these differences, it would not be surprising to find that factors that drive differences across the entire US differ from those that drive differences across urban areas. These results will be important, because previous research has focused almost exclusively on urban areas to develop ideas for why some individuals are evicted and others are not. If the factors that drive differences in eviction rates are different in urban areas than the rest of the United States, the policies that we use to decrease eviction rates will also need to be different.

Methods

I use regression analysis to explore the relationship between eviction filing rates and eviction judgments and possible predictors in both the full sample and the urban sample. The distribution of the eviction filing rate and the eviction judgment rate suggest that ordinary least squares may not be the best estimation method for the data. In Figures 6.1 and 6.2, I plot histograms of the eviction filing rate and the eviction judgment rate, respectively. In both figures, the histograms are right skewed with pile-up near zero. For the eviction filing rate, 2,640 observations (approximately 9.3 percent of the sample) equal zero. For the eviction judgment rate, 3,284 observations (approximately 11.6 percent of the sample) equal zero. These characteristics of the data will be accounted for in the empirical specifications that follow.

Figure 6.1 Histogram of the Eviction Filing Rate





Because the data are skewed, it is at first appealing to estimate the above model using Tobit regression. Tobit is used in situations where the outcome variable is censored or where there is a corner solution. My outcomes are not censored and, since they are rates, are not corner solutions, but they are restricted to have a lower bound of zero.

As rates, both the eviction filing rate and the eviction judgment rate are considered proportions, which are bounded between zero and one. Although the eviction filing rate can technically go above one, in the samples I use in this analysis, the data never goes above one. To account for the fractional nature of the outcome variables, I estimate a fractional response model. The fractional response model uses a logit Quasi-Maximum Likelihood Estimator to estimate the following nonlinear model:

$$Y_{it} = G(X_{it}\beta + E_{it}\delta + G_{it}\gamma + T_t + u_{it}),$$

where Y_{it} is the eviction filing rate or the eviction judgement rate in county *i* in year *t*; $G(\cdot)$ is the logistic function; X_{it} is a vector of demographic covariates including county *i*'s percentage of black residents, percentage of Hispanic residents, degree of black-white racial residential segregation, percentage of female headed households, and educational attainment composition in year *t*; E_{it} is a vector of economic covariates including county *i*'s median gross rent, median household income, and percent of families in poverty in year *t*; G_{it} is a geographic control equal to 1 if county *i* is urban (population greater than or equal to 50,000) in year *t* and 0 otherwise, T_t is a vector of time dummy variables, and u_{it} is an error term for county *i* in year *t*.

Results

All Counties

I begin with the full sample results. In Table 6.2, I present results from the QMLE regression of the eviction filing rate on its covariates. In column 1, I present the QMLE estimates of the fractional response model. Because the coefficients are not directly interpretable, in column 2, I present the QMLE estimates as odds ratios. Because expected eviction filing rates and expected eviction judgment rates can be viewed as estimates of the probability of an eviction filing or an eviction judgment, it is possible to adopt an odds-ratio interpretation of the results (Stata, n.d.). Odds ratios are interpreted in relation to one. An odds ratio greater than one indicates that the covariate increases the odds of the outcome, an odds ratio equal to one indicates that the covariate has no effect on the odds of the outcome, and an odds ratio less than one indicates that the covariate decreases the odds of the outcome (Szumilas, 2010).

The coefficients in column 1 suggest that both demographic and economic factors are associated with differences in eviction filing rates across US counties. The percent of black residents, percent of female-headed households, percent of the population over 25 with less than a high school, percent of the population over 25 with a high school degree, the median gross rent, the unemployment rate, and the county being urban are all positively associated with the eviction filing rate and statistically significant. The percent of Hispanic residents and the percent of families living in poverty are both negatively associated with the eviction filing rate and statistically significant.

In column 2, the odds ratios for the percent of black residents, the percent of Hispanic residents, percent of female-headed households, the median gross rent, the percent of families living in poverty, the unemployment rate, aand the county being urban are the most precisely estimated, because the confidence intervals are the smallest (Szumilas, 2010). Of these, the percent of female-headed households, the median gross rent, and the county being urban are most strongly associated with eviction filings, because the odds ratios are the largest or smallest. The odds of an eviction filing are 1.08 higher given a one unit increase in the percent of female-headed households in a county. The odds of an eviction filing are 1.17 higher given a one unit increase in the median gross rent in a county. The odds of an eviction filing are 2.42 higher given an urban county compared to a rural county.

Table 6.2
The Eviction Filing Rate and Its Covariates

	Fractional Response Coefficients	Fractional Response Odds Ratios
% Black	0.0217***	1.022***
	(0.002)	[1.018,1.026]
% Hispanic	-0.0152***	0.985***
	(0.002)	[0.980,0.990]
Dissimilarity Index	-0.0332	0.967
	(0.115)	[0.772,1.212]
% Female-Headed Households	0.0802***	1.084***
	(0.009)	[1.065,1.103]
% < HS Grad	0.0256**	1.026*

	(0.011)	[1.004,1.048]
% HS Grad	0.0243**	1.025*
	(0.010)	[1.006,1.044]
% Some College	0.0143	1.014
	(0.009)	[0.997,1.032]
% College Grad	0.0104	1.010
	(0.016)	[0.980,1.042]
Median Gross Rent ($ 100s)	0.160***	1.174***
	(0.020)	[1.129,1.220]
Median Household Income ($ 1000s)	-0.000824	0.999
	(0.003)	[0.993,1.005]
% Families in Poverty	-0.0586***	0.943***
	(0.008)	[0.929,0.957]
Unemployment Rate (%)	0.0509***	1.052***
	(0.008)	[1.035,1.070]
Urban	0.884***	2.420***
	(0.055)	[2.174,2.693]
Observations	28,306	28,306

In Table 6.3, I present results from the QMLE regression of the eviction judgment rate on its covariates. In column 1, I present the QMLE estimates of the fractional response model; in column 2, I present the QMLE estimates as odds ratios. The coefficients in column 1 again suggest that both demographic and economic factors are associated with differences in eviction judgment rates across US counties. The percent of black residents, the degree of black-white racial residential segregation, percent of female-headed households, the percent of the population over 25 with less than a high school, the percent of the population over 25 with a high school degree, the percent of the population over 25 with some college, the median gross rent, the unemployment rate, and the county being urban are all positively associated with the eviction judgment rate and statistically significant. The percent of Hispanic residents, the median household income, and the percent of families living in poverty are all negatively associated with the eviction filing rate and statistically significant.

In column 2, the odds ratios for the percent of black residents, the percent of Hispanic residents, the percent of female-headed households, the median gross rent, the percent of families living in poverty, the unemployment rate, are the county being urban are the most precisely estimated. Of these, the percent of female-headed households, the median gross rent, and the county being urban are most strongly associated with eviction filings. The odds of an eviction judgment are 1.08 higher given a one unit increase in the percent of female-headed households in a county. The odds of an eviction judgment are 1.13 higher given a one unit increase in the median gross rent in a county. The odds of an eviction judgment are 1.99 higher given an urban county compared to a rural county.

Table 6.3
The Eviction Judgment Rate and Its Covariates

	Fractional Response Coefficients	Fractional Response Odds Ratios
% Black	0.00844***	1.008***
	(0.002)	[1.005,1.012]
% Hispanic	-0.0131***	0.987***
	(0.002)	[0.983,0.991]
Dissimilarity Index	0.199**	1.220*
	(0.094)	[1.015,1.466]
% Female-Headed Households	0.0803***	1.084***
	(0.007)	[1.068,1.099]
% < HS Grad	0.0165*	1.017
	(0.009)	[1.000,1.034]
% HS Grad	0.0127*	1.013
	(0.007)	[0.998,1.028]
% Some College	0.0154**	1.015*
	(0.007)	[1.002,1.029]

% College Grad	-0.00897	0.991
	(0.012)	[0.967,1.016]
Median Gross Rent ($ 100s)	0.125***	1.133***
	(0.016)	[1.098,1.170]
Median Household Income ($ 1000s)	-0.00435*	0.996
	(0.003)	[0.991,1.001]
% Families in Poverty	-0.0463***	0.955***
	(0.006)	[0.944,0.966]
Unemployment Rate (%)	0.0272***	1.028***
	(0.007)	[1.013,1.042]
Urban	0.690***	1.994***
	(0.042)	[1.835,2.166]
Observations	28,306	28,306

Urban Counties

In Table 6.4, I present results from the QMLE regression of the eviction filling rate on its covariates for urban counties. In column 1, I present the QMLE estimates of the fractional response model; in column 2, I present the QMLE estimates as odds ratios. The coefficients in column 1 again suggest that both demographic and economic factors are associated with differences in eviction filing rates across urban US counties. The percent of black residents, percent of female-headed households, the percent of the population over 25 with less than a high school, the percent of the population over 25 with a high school degree, the percent of the population over 25 with some college, the percent of the population over 25 with a college degree, and the unemployment rate are all positively associated with the eviction filing rate and statistically significant. The degree of black-white racial residential segregation and the percent of families living in poverty are both negatively associated with the eviction filing rate and statistically significant.

In column 2, the odds ratios for the percent of black residents, the degree of black-white racial residential segregation, the percent of female-headed households, the percent of the population over 25 with less than a high school, the percent of the population over 25 with a high school degree, the percent of the population over 25 with a college degree, the percent of families living in poverty, the unemployment rate, and the county being urban are the most precisely estimated. Of these, the degree of black-white racial residential segregation, the percent of families living in poverty, and the unemployment rate are most strongly associated with eviction filings. The odds of an eviction filing are 0.49 lower given a one unit increase in the dissimilarity index in a county. The odds of an eviction filing are 0.919 lower given a one unit increase in the percent of families living in poverty in a county. The odds of an eviction filing are 1.09 higher given a one unit increase in the eviction filing rate.

Table 6.4
The Eviction Filing Rate and Its Covariates, Urban Counties

	Fractional Response Coefficients	Fractional Response Odds Ratios
% Black	0.0381***	1.039***
	(0.003)	[1.032,1.046]
% Hispanic	-0.00528	0.995
	(0.004)	[0.987,1.003]
Dissimilarity Index	-0.718***	0.488**
	(0.228)	[0.312,0.763]
% Female-Headed Households	0.0691***	1.072***
	(0.015)	[1.040,1.104]
% < HS Grad	0.0476***	1.049**
	(0.016)	[1.016,1.083]
% HS Grad	0.0473***	1.048***
	(0.013)	[1.021,1.076]
% Some College	0.0296**	1.030*
	(0.012)	[1.006,1.055]

% College Grad	0.0626***	1.065**
	(0.022)	[1.020,1.111]
Median Gross Rent ($ 100s)	0.0204	1.021
	(0.026)	[0.971,1.073]
Median Household Income ($ 1000s)	0.00380	1.004
	(0.004)	[0.996,1.012]
% Families in Poverty	-0.0849***	0.919***
	(0.017)	[0.889,0.949]
Unemployment Rate (%)	0.0860***	1.090***
	(0.012)	[1.065,1.115]
Observations	8,910	8,910

In Table 6.5, I present results from the QMLE regression of the eviction judgment rate on its covariates for urban counties. In column 1, I present the QMLE estimates of the fractional response model; in column 2, I present the QMLE estimates as odds ratios. The coefficients in column 1 again suggest that both demographic and economic factors are associated with differences in eviction judgment rates across urban US counties. The percent of black residents, percent of female-headed households, the percent of the population over 25 with a high school degree, the percent of the population over 25 with some college, the median household income, and the unemployment rate are all positively associated with the eviction filing rate and statistically significant. The median gross rent and the percent of families living in poverty are both negatively associated with the eviction filing rate and statistically significant.

In column 2, the odds ratios for the percent of black residents, the percent of female-headed households, the percent of the population over 25 with a high school degree, and the unemployment rate are the most precisely estimated. Of these, the percent of female-headed households is the most strongly associated with eviction judgments. The odds of an eviction judgment are 1.067 higher given a one unit increase in the percent of female-headed households in a county.

Table 6.5
The Eviction Judgment Rate and Its Covariates, Urban Counties

	Fractional Response Coefficients	Fractional Response Odds Ratios
% Black	0.0195***	1.020***
	(0.003)	[1.014,1.025]
% Hispanic	-0.00320	0.997
	(0.003)	[0.991,1.003]
Dissimilarity Index	-0.263	0.769
	(0.219)	[0.500,1.181]
% Female-Headed Households	0.0645***	1.067***
	(0.013)	[1.039,1.095]
% < HS Grad	0.0212	1.021
	(0.014)	[0.994,1.049]
% HS Grad	0.0300***	1.030**
	(0.011)	[1.008,1.053]
% Some College	0.0433***	1.044***
	(0.010)	[1.023,1.066]
% College Grad	0.0294	1.030
	(0.019)	[0.993,1.069]
Median Gross Rent ($ 100s)	-0.0412*	0.960
	(0.021)	[0.921,1.000]
Median Household Income ($ 1000s)	0.00856**	1.009*
	(0.004)	[1.001,1.016]
% Families in Poverty	-0.0315**	0.969*
	(0.014)	[0.943,0.996]
Unemployment Rate (%)	0.0383***	1.039***
	(0.011)	[1.016,1.063]
Observations	8,910	8,910

Robustness

Full Sample. The main results are robust to changes in the full sample. The full sample was an unbalanced panel. To confirm that the main results do not depend on the unbalanced panel, I repeat the analysis on a balanced panel. The balanced panel includes only counties observed for the entire 2005-2016 period. Summary statistics for the original, unbalanced full panel, are reprinted in columns 1-4 of Table 6.6 for convenience. Summary statistics for the balanced panel are printed in columns 5-8 of Table 6.8. As shown, the means are nearly identical across the two samples.

Table 6.6
Robustness of Summary Statistics

	Unbalanced Panel				Balanced Panel			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Eviction Filing Rate	0.0344	0.0490	0.0000	0.5480	0.0330	0.0463	0.0000	0.5480
Eviction Judgment Rate	0.0179	0.0201	0.0000	0.2416	0.0176	0.0197	0.0000	0.1980
% Black	9.02	14.36	0.01	86.76	9.03	14.37	0.01	86.76
% Hispanic	8.30	13.11	0.00	95.54	7.96	12.54	0.00	95.54
Dissimilarity Index	0.41	0.18	0.00	0.99	0.42	0.18	0.00	0.99
% Female-Headed Households	9.54	3.52	0.00	29.60	9.53	3.51	0.00	29.60
% < HS Grad	16.03	7.17	1.26	48.70	16.15	7.15	2.85	48.70
% HS Grad	35.52	6.98	7.52	55.10	35.87	6.93	10.26	55.10
% Some College	29.08	5.30	10.83	48.82	28.93	5.23	10.83	46.77
% College Grad	12.67	5.34	2.50	42.20	12.47	5.31	2.50	42.20
Median Rent (100s)	7.14	1.86	1.99	19.40	7.08	1.82	1.99	19.40
Median Income (1000s)	48.33	12.38	19.58	139.58	48.20	12.21	19.58	137.99
% Families in Poverty	11.87	5.44	0.49	44.32	11.85	5.42	0.49	44.32
Unemployment Rate (%)	6.77	2.96	0.20	26.30	6.76	2.93	0.30	26.30
Urban (%)	0.31	0.46	0.00	1.00	0.30	0.46	0.00	1.00
Observations	28,306				23,436			

I estimate the primary specification, the fractional response model, on the balanced panel. The results for the unbalanced panel are presented in columns (1) and (3) for convenience. The results for the balanced panel are presented in columns (2) and (4). As shown, the results are robust. The directions of all coefficients are identical across both outcomes, while the magnitudes are nearly identical across both outcomes. Therefore, the main results do not depend on the unbalanced panel.

Table 6.7
Robustness of the Eviction Rates and Their Covariates

	Eviction Filing Rate		Eviction Judgment Rate	
	Unbalanced	Balanced	Unbalanced	Balanced
% Black	0.0217***	0.0173***	0.00844***	0.00626***
	(0.0020)	(0.0023)	(0.0016)	(0.0018)
% Hispanic	-0.0152***	-0.0165***	-0.0131***	-0.0155***
	(0.0024)	(0.0028)	(0.0019)	(0.0023)
Dissimilarity Index	-0.0332	0.0625	0.199**	0.191*
	(0.1149)	(0.1262)	(0.0939)	(0.1047)
% Female-Headed Households	0.0802***	0.0947***	0.0803***	0.0897***
	(0.0089)	(0.0101)	(0.0073)	(0.0082)
% < HS Grad	0.0256**	0.0291**	0.0165*	0.0200*
	(0.0109)	(0.0131)	(0.0086)	(0.0102)
% HS Grad	0.0243**	0.0251**	0.0127*	0.0150*
	(0.0095)	(0.0118)	(0.0075)	(0.0090)
% Some College	0.0143	0.0160	0.0154**	0.0210**
	(0.0089)	(0.0110)	(0.0070)	(0.0084)
% College Grad	0.0104	0.0136	-0.00897	-0.00418
	(0.0158)	(0.0196)	(0.0125)	(0.0151)
Median Gross Rent ($ 100s)	0.160***	0.186***	0.125***	0.143***
	(0.0196)	(0.0224)	(0.0162)	(0.0187)
Median Household Income ($ 1000s)	-0.000824	-0.00182	-0.00435*	-0.00585**
	(0.0030)	(0.0034)	(0.0026)	(0.0028)
% Families in Poverty	-0.0586***	-0.0642***	-0.0463***	-0.0504***
	(0.0076)	(0.0082)	(0.0060)	(0.0067)
Unemployment Rate (%)	0.0509***	0.0438***	0.0272***	0.0256***
	(0.0084)	(0.0086)	(0.0070)	(0.0079)

Urban	0.884***	0.856***	0.690***	0.701***
	(0.0545)	(0.0610)	(0.0423)	(0.0473)
Observations	28,306	23,436	28,306	23,436

Urban. The urban results are robust to changes in the underlying data. The ACS contains 5-year, 3-year, and 1-year estimates. However, the 5-year estimates are the only estimates available for all US counties. The 3-year estimates are only available for areas with a population of 20,000 or more, while the 1-year estimates are only available for areas with a population of 65,000 or more (Census, 2020). To confirm that the urban results do not depend on estimates that change only once every five years, I construct an urban sample using the 1-year estimates. I also reduce my original urban sample to the same 2,177 county-year observations to compare the results. Summary statistics for the restricted original sample and the new urban sample are presented in Table 6.8 below. As shown, the eviction filing rate, the eviction judgment rate, and the unemployment rate are identical in both samples. This is because these are the only variables that change every year in the original urban sample. These should be the same since we have restricted the samples to the same counties. The rest of the summary statistics appear nearly identical across samples.

Table 6.8
Robustness of Summary Statistics, Urban Counties, 2010-2016

	5-Year Estimates				1-Year Estimates			
	Mean	SD	Min	Max	Mean	SD	Min	Max
Eviction Filing Rate	0.0939	0.0769	0.0005	0.4944	0.0939	0.0769	0.0005	0.4944
Eviction Rate	0.0363	0.0243	0.0000	0.1613	0.0363	0.0243	0.0000	0.1613
% Black	14.19	13.32	0.05	72.49	14.14	13.28	0.29	70.31
% Female-Headed Households	11.38	3.38	2.54	23.03	11.34	3.17	5.40	27.02
% < HS Grad	12.17	4.39	1.52	34.52	12.21	4.24	2.32	37.91
% HS Grad	30.48	6.87	9.16	52.14	30.45	6.73	8.30	50.89
% Some College	29.80	4.60	10.48	46.12	29.80	4.37	12.29	43.10
% College Grad	17.47	5.53	4.99	37.00	17.46	5.40	5.84	37.78
Median Gross Rent (100s, 2016 $)	8.58	1.84	4.53	18.58	8.68	1.82	5.23	18.68

Median Household Income (1000s, 2016 $)	53.85	12.88	29.63	134.46	53.68	12.62	31.00	125.05
% Families in Poverty	11.29	4.26	2.02	33.33	11.25	4.02	2.58	29.93
Unemployment Rate	7.17	2.32	2.60	19.00	7.17	2.32	2.60	19.00
Observations		2,177				2,177		

I estimate the fractional response model on both urban samples. The results for the restricted original sample are presented in columns (1) and (3). The results for the new urban sample are presented in columns (2) and (4). As shown, the results are robust. The directions and magnitudes of all coefficients are nearly identical across both outcomes. Therefore, the main urban results do not depend on the 5-year estimates.

Table 6.9
Robustness of the Eviction Rates and Their Covariates, Urban Counties, 2010-2016

	Eviction Filing Rate		Eviction Judgment Rate	
	5-Year	1-Year	5-Year	1-Year
% Black	0.0378***	0.0375***	0.0157***	0.0187***
	(0.0044)	(0.004)	(0.0032)	(0.002)
% Female-Headed Households	0.0427*	0.0153	0.0673***	0.0298***
	(0.0223)	(0.011)	(0.0194)	(0.010)
% < HS Grad	0.0791***	0.0544***	0.0172	0.0136
	(0.0174)	(0.014)	(0.0156)	(0.012)
% HS Grad	0.0344**	0.0368***	0.00336	0.0143
	(0.0165)	(0.013)	(0.0139)	(0.011)
% Some College	0.0516***	0.0493***	0.0471***	0.0502***
	(0.0144)	(0.012)	(0.0121)	(0.010)
% College Grad	0.0491*	0.0408**	-0.00326	0.0115
	(0.0267)	(0.020)	(0.0234)	(0.017)
Median Gross Rent ($ 100s)	0.0792**	0.0761***	-0.0608**	-0.0450*
	(0.0315)	(0.029)	(0.0273)	(0.024)
Median Household Income ($ 1000s)	-0.00853	0.00203	0.000446	0.00114
	(0.0061)	(0.005)	(0.0053)	(0.004)

% Families in Poverty	-0.127***	-0.0613***	-0.0599***	-0.0243**
	(0.0245)	(0.012)	(0.0221)	(0.011)
Unemployment Rate (%)	0.0693***	0.0547***	0.00392	-0.00507
	(0.0194)	(0.020)	(0.0201)	(0.020)
Observations	2,177	2,177	2,177	2,177

Discussion

There is a large variation in eviction rates across US counties. This chapter provides a first step in understanding why. Prior literature suggested that both demographics and economics contribute to differences in eviction outcomes. However, these studies have drawn conclusions from data from one city or county. Further, these studies have focused on urban areas exclusively. I find that county-level demographic composition and economic conditions are associated with differences in eviction rates. I find that there are a lot of similarities between the factors that explain filing and judgment rates, as well as the full sample versus the urban sample. However, not all factors are exactly the same or of the same importance.

These results suggest three aspects that need to be considered when developing policies to reduce evictions: geography, outcomes, and factors associated with outcomes. First, we need to consider whether we are addressing evictions in an urban are or not. Factors associated with eviction rates differ across geographies, so programs need not be the same across the entire US. Second, we need to consider the outcome we are trying to address. Programs that address eviction judgements may not address eviction filings. For example, a number of eviction diversion programs exist in the US, some of which offer to pay the back rent owed by a tenant to prevent an eviction. Although this may prevent an eviction judgement, it does not prevent an eviction filing. Lastly, we need to be aware of the demographic and economic factors that affect eviction rates.

These results suggest that policies need to be targeted to local conditions. National policy would likely only be sufficient if it allowed for localities to be able to tailor their program to their area. This reflects the current state of national housing policy. For example, housing vouchers are a national program, but the vouchers are administered locally, and the amounts of the vouchers are targeted to local housing markets. These results do create a challenge for those who want to replicate an existing program. Because the factors that affect eviction differ depending on geography and outcome, a program that works well in one locality may not work well in another if the conditions are not the same. A final challenge is that both demographic and economic conditions affect evictions, but we often only consider the economic factors when creating solutions. The previously mentioned eviction diversion programs address economic issues, as do solutions like affordable housing. It is more difficult to come up with solutions to address demographic factors, specifically race.

The racial demographic results in this paper cannot speak to discrimination, because of the aggregate nature of the data. However, if discrimination is a part of the explanation for these results, it creates an additional challenge for policy makers. Landlords cannot file a legal eviction based on an individual's race (or gender or family status), so discrimination in eviction filings and eviction judgements would result from landlords and possibly even courts making different decisions on when to file or evict based off of an individual's demographic characteristics. We would need to ensure that landlords and courts were making eviction filing and eviction judgement decisions the same across all people in a similar situation. A potential solution might be similar to that of the Home Mortgage Disclosure Act (HMDA) for mortgages. All landlords and courts could be required to report their eviction outcomes to an organization that collects the data to determine if there is statistical discrimination.

Conclusion

The factors associated with differences in eviction rates fall into two broad categories: demographics and economics. These categories are consistent with those found by the previous literature. However, this chapter has extended the previous literature in several ways. First, it has confirmed that the idea that demographics and economics play a role in eviction outcomes holds across the US. These results suggest that policymakers need to consider both economics and demographics when crafting policies. The demographic results suggest that discrimination could be at work, as I have controlled for a number of economic factors.

This chapter has also shown that different factors affect eviction filing rates versus eviction judgement rates. Further, the factors that affect eviction in urban areas are different than those that affect eviction in rural areas. This result seems intuitive, as different parts of the US have different rental housing markets and demographics and economics. This chapter has suggested that national policy may only be effective in reducing the eviction crisis if it allows localities to tailor programs to their local conditions: including the outcomes that are a problem in their local and the factors associated with it.

The goal of this chapter is to provide an understanding of the variation in eviction in the US. It is important to understand what drives differences in eviction rates, before trying to solve the problem of high eviction rates, because a clear understanding of the problem helps us to create the most effective solutions. It is impossible to solve a problem that you do not understand.

CHAPTER VII

THE EFFECT OF UI BENEFITS ON EVICTION

Chapter VI established predictors of variation in eviction filing rates and eviction judgment rates across the country. One of those predictors, unemployment, is of particular interest during the ongoing coronavirus pandemic. In April 2020, the US unemployment rate reached 14.7 percent, up from 4.4 percent the month before (BLS, 2020). The high level of unemployment associated with the coronavirus pandemic has been particularly hard on renters. According to the Week 25 Household Pulse Survey (February 17-March 1, 2021), a new experimental survey that collects data on how the coronavirus pandemic impacts people's lives, over 23 million renter households contain a respondent who is unemployed (US Census Bureau, 2021). Of those 23 million, over 5 million renter households remain behind on their rent payments. High unemployment places renters in precarious positions; unemployment increases the likelihood of missed rental payments and nonpayment of rent is a reason to file for eviction in all fifty states.

A key motivation for policy intervention is to avoid the additional unseen costs of eviction borne by renters, landlords, taxpayers, and those in the surrounding community. A program that has the potential to aid renters in the ongoing eviction crisis is unemployment insurance (UI). Most evictions are filed for nonpayment of rent, which can result from employment instability or job loss (Sills et al., 2018). As a result, UI has the potential to serve as an eviction prevention program by mitigating the effect of unemployment on eviction.

In this chapter, I explore the effect of UI benefits on eviction filings. Using data from nearly all US counties from 2002-2016, I estimate the effect of state-level UI benefits on county-level eviction filing rates. My identification strategy rests on the exogeneity of variation in UI benefits within states over time. Despite what intuition may indicate, I find that when UI benefits are low, an increase in the county-level unemployment rate decreases eviction filings. By contrast, when UI benefits are high, an increase in the unemployment rate increases eviction filings. These results are robust to changes in the specification and although perhaps counterintuitive, are consistent with the literature on landlord-tenant interactions, particularly serial evictions, as well as predictions from my theoretical model from Chapter III.

This chapter contributes to the growing body of literature on eviction in several ways. First, it focuses on eviction prevention, which has yet to be thoroughly addressed in the literature. Second, it highlights the importance of studying eviction filings, which have been focused on less in the literature than eviction judgments. Lastly, it addresses the importance of understanding landlord-tenant relationships, particularly from the landlord's perspective.

Overall, my results suggest that the effectiveness of eviction prevention programs lies in creating them with a clear understanding of landlord-tenant interactions. If we want to create effective eviction prevention policies, we need to understand the mechanisms through which evictions take place. These results provide useful information for policymakers as they attempt to address the ongoing eviction crisis.

Background

Eviction

Although much of the prior literature focuses on eviction judgments, this paper follows the recent trend in the literature to focus on eviction filings. This new focus on eviction filings is important. First, not all filings lead to judgments, which means more households are affected by filings (Garboden and Rosen, 2019). The Eviction Lab records eviction filings and eviction judgements from 2000 to 2016 (Desmond et al., 2018a). Columns 2 and 3 in Table 7.1 present the number of eviction filings and eviction judgments, respectively. In column 4, I calculate the likelihood of eviction, the percentage of eviction filings that result in eviction judgments. I find that less than half of all filings result in a judgment. A study in Washington, DC found that in 2018, only about 5.5 percent of filings resulted in a judgment (McCabe and Rosen, 2020). If we ignore eviction filings, we are ignoring the largest part of the eviction process.

Table 7.1
The Percentage of Eviction Filings that Result in Eviction Judgments over Time

Year	Eviction Filings	Eviction Judgments	Likelihood of Eviction (%)
2002	2,085,491	864,918	41
2003	2,134,014	910,361	43
2004	2,177,018	940,817	43
2005	2,306,580	969,303	42
2006	2,441,067	1,019,600	42
2007	2,002,531	958,605	48
2008	2,079,865	996,233	48
2009	2,108,719	952,699	45
2010	2,374,084	993,531	42
2011	2,452,080	987,999	40
2012	2,420,135	983,666	41
2013	2,378,464	930,693	39
2014	2,394,318	908,977	38
2015	2,288,732	870,325	38
2016	2,350,042	898,479	38

Source: Eviction Filings and Eviction Judgments come from the Eviction Lab national-level data.
Notes: Eviction filings is equal to the total number of eviction filings in the United States each year, including those filed against the same household. Eviction judgments is equal to the total number of eviction judgments in the United States each year. Filings to Judgments equals column 3 divided by column 2 multiplied by 100. Column 4 is rounded to the nearest whole percent.

Second, the threat of eviction embodied by filings has been tied to its own set of negative consequences. The threat of eviction has been shown to cause stress and financial strain for families (Vasquez-Vera, 2016; Sills et al., 2018; Immergluck et al., 2019). Additionally, it can lead some tenants to offer up favors, such as labor or sex, to work off debt (Garboden and Rosen, 2019). Tenants can also be less likely to seek help in situations of domestic violence or housing code violations (Garboden and Rosen, 2019). By focusing only on eviction judgments, the prior literature may not have captured the full impact of the eviction process on those that experience it (Garboden and Rosen, 2019).

Third, by preventing eviction filings, we can prevent eviction judgments. Existing prevention methods, like emergency rental assistance or access to legal aid, focus on preventing judgments, not filings. These services are often not available until a tenant receives an eviction filing. Although these programs have been successful in avoiding some eviction judgments, they are not always successful at keeping tenants in their homes. Sometimes the removal of a tenant cannot be avoided, so these services are negotiating better terms for the removal like giving the tenant more time to move out (LANC, 2017). By focusing on the front end of the eviction process, we may be better able to address eviction judgments.

To prevent eviction filings, we need to be considering the entire eviction process. Most eviction cases are filed for nonpayment of rent (Sills et al., 2018; Urban Institute at UNCC, 2018; McCabe and Rosen, 2020). If landlords wish to ensure that they receive their rent, they must file for eviction. Additionally, filing for eviction often allows landlords the opportunity to charge the tenant with late fees, which has been shown to increase the tenant’s costs by as much as 20% (Leung, et al., 2020). Further, if the tenant does indeed continue to miss their rental payments, filing for eviction is the only way for landlords to legally ensure that they can remove the tenant from their property. These outcomes suggest that eviction prevention that focuses only on the tenant is inherently flawed. Eviction is a process that involves two parties: the landlord and the tenant. There needs to be a concern for the landlords' actions as well, not just the tenant (McCabe and Rosen, 2020).

Unemployment Insurance

Unemployment insurance is a social insurance program that aims to assist individuals who have lost their jobs while they look for a new one. The program consists of two types of benefits: regular benefits and extended benefits. The regular benefits program is run by the states and overseen by the United States Department of Labor. It is a state-federal partnership where the states have primary control. Regular benefits are available to the unemployed regardless of economic conditions. During economic downturns, additional programs can be enacted. The states, the federal government, or both can run these extended benefits programs. Extended benefits are only available to the unemployed during poor economic conditions.

Regular Benefits. Regular UI benefits can broadly be characterized by the weekly benefit amount and benefit duration. The weekly benefit amount is how much an individual receives in benefits each week. The benefit duration is the number of weeks an individual can receive benefits. Each state sets its own maximum weekly benefit amount and maximum benefit duration, the highest weekly benefit amount, and the highest number of weeks of benefits an individual can obtain. Although the maximum weekly benefit amount varies greatly across states, the maximum benefit duration is typically 26 weeks. Regular UI benefits tend to replace about half of a workers' lost wages.

Table 7.2 shows the change in the maximum weekly benefit amount and the maximum benefit duration in each state from 2002 to 2016. The maximum weekly benefit amount varies greatly across states and time with some states reducing their maximum weekly benefit while others have maintained or increased it. For example, North Carolina had a maximum weekly benefit amount of $396 in 2002, but only $350 in 2016, not adjusted for inflation. This increase is equivalent to about a 12 percent decrease in the nominal maximum weekly benefit amount. The opposite extreme, North Dakota, provided a maximum weekly benefit amount of only $290 in 2002, but increased it by about 118 percent by 2016 to provide $633. Unlike maximum benefit amount, there is much less variation in maximum benefit duration. The smallest maximum benefit duration decreased from 26 weeks to 12 weeks from 2002 to 2016 in Florida, while the largest maximum benefit duration remained at 30 weeks in Massachusetts.

Table 7.2
The Change in UI Benefits over Time by State

	Maximum Weekly Benefit Amount			Maximum Benefit Duration		
State	2002	2016	% Change	2002	2016	% Change
AL	190	265	39%	26	26	0%
AZ	205	240	17%	26	26	0%
AR	333	451	35%	26	20	-23%
CA	330	450	36%	26	26	0%
CO	390	552	42%	26	26	0%
CT	481	673	40%	26	26	0%
DE	330	330	0%	26	26	0%
FL	275	275	0%	26	12	-54%
GA	284	330	16%	26	14	-46%
ID	315	410	30%	26	26	0%
IL	431	595	38%	26	25	-4%
IN	312	390	25%	26	26	0%
IO	347	529	52%	26	26	0%
KS	333	474	42%	26	16	-38%
KY	329	415	26%	26	26	0%
LA	258	247	-4%	26	26	0%
ME	408	595	46%	26	26	0%
MA	768	1083	41%	30	30	0%
MI	300	362	21%	26	20	-23%
MN	452	658	46%	26	26	0%
MS	200	235	18%	26	26	0%
MO	250	320	28%	26	13	-50%
MT	286	487	70%	26	28	8%
NE	262	392	50%	26	26	0%

NV	301	417	39%	26	26	0%
NH	331	427	29%	26	26	0%
NJ	446	657	47%	26	26	0%
NM	277	473	71%	26	26	0%
NY	405	420	4%	26	26	0%
NC	396	350	-12%	26	13	-50%
ND	290	633	118%	26	26	0%
OH	414	587	42%	26	26	0%
OK	304	505	66%	26	26	0%
OR	400	549	37%	26	26	0%
PA	438	581	33%	26	26	0%
RI	518	707	36%	26	26	0%
SC	268	326	22%	26	20	-23%
SD	234	366	56%	26	26	0%
TN	275	275	0%	26	26	0%
TX	319	479	50%	26	26	0%
UT	365	509	39%	26	26	0%
VT	312	446	43%	26	26	0%
VA	268	378	41%	26	26	0%
WA	496	664	34%	30	26	-13%
WV	338	424	25%	26	26	0%
WI	324	370	14%	26	26	0%
WY	283	491	73%	26	26	0%

Source: Maximum Weekly Benefit Amount (WBA) and Maximum Benefit Duration come from the January publications of the US Department of Labor Employment & Training Administration's Significant Provisions of State UI Laws.
Notes: Maximum WBA is equal to the highest value listed for each state. Dollar values in columns 2-3 are nominal. Duration values in columns 5-6 are in weeks. Columns 4 and 7 are rounded to the nearest whole percent.

If UI benefits are to aid in eviction prevention, it would be through replacement of workers' lost wages. Table 7.3 depicts the potential impact of UI on renters in each state. Column 1 contains the median renter household income (monthly); column 2, the potential unemployment insurance benefit (monthly); column 3, the median gross rent (monthly), and column 4, the maximum benefit duration (weeks). Column 5 calculates the potential impact of UI on renters through the median gross rent as a percentage of unemployment insurance benefits. Across all 50 states, rent makes up less than 100% of monthly UI benefits. This result indicates that, in all states, monthly UI benefits have the potential to cover monthly rent. However, some states benefits are far more likely to cover rent than others. For example, Arizona's median gross rent takes up 94% of monthly UI benefits, whereas North Dakota's median gross rent takes up only 48% of monthly UI benefits.

Table 7.3 The Potential Value of UI Benefits to Renters

State	Median Household Income	Potential UI Benefit	Median Gross Rent	UI Rent Burden	Maximum Coverage
AL	2,249	1,124	743	66%	6
AK	4,483	1,914	1,208	63%	6
AZ	3,212	1,039	976	94%	6
AR	2,378	1,189	701	59%	4.62
CA	3,936	1,949	1,375	71%	6
CO	3,516	1,758	1,171	67%	6
CT	3,336	1,668	1,115	67%	6
DE	3,122	1,429	1,048	73%	6
DC	4,235	1,554	1,376	89%	6
FL	3,055	1,191	1,086	91%	2.77
GA	2,990	1,429	933	65%	3.23
HI	4,594	2,297	1,483	65%	6
ID	2,691	1,346	790	59%	6
IL	3,033	1,516	950	63%	5.77
IN	2,594	1,297	768	59%	6
IO	2,642	1,321	741	56%	6
KS	2,849	1,424	789	55%	3.7
KY	2,363	1,182	707	60%	6
LA	2,224	1,070	808	76%	6
ME	2,543	1,272	797	63%	6
MD	4,140	1,862	1,314	71%	6
MA	3,448	1,724	1,179	68%	6.93
MI	2,564	1,282	818	64%	4.62
MN	3,064	1,532	912	60%	6
MS	2,272	1,018	728	72%	6
MO	2,706	1,353	771	57%	3
MT	2,714	1,357	741	55%	6.47
NE	2,777	1,388	769	55%	6
NV	3,263	1,632	1,003	61%	6

NH	3,589	1,794	1,026	57%	6
NJ	3,713	1,857	1,244	67%	6
NM	2,498	1,249	804	64%	6
NY	3,411	1,706	1,194	70%	6
NC	2,718	1,359	839	62%	3
ND	3,216	1,608	776	48%	6
OH	2,587	1,293	759	59%	6
OK	2,614	1,307	744	57%	6
OR	3,110	1,555	1,015	65%	6
PA	2,863	1,432	881	62%	6
RI	2,782	1,391	948	68%	6
SC	2,637	1,318	841	64%	4.62
SD	2,657	1,329	706	53%	6
TN	2,634	1,191	806	68%	6
TX	3,244	1,622	956	59%	6
UT	3,430	1,715	954	56%	6
VT	2,709	1,355	925	68%	6
VA	3,664	1,637	1,159	71%	6
WA	3,757	1,879	1,135	60%	6
WV	2,169	1,085	682	63%	6
WI	2,820	1,410	802	57%	6
WY	3,236	1,618	840	52%	6

Source: Calculations based on 2016 American Community Survey and the January 2016 publication of the US Department of Labor Employment & Training Administration's Significant Provisions of State UI Laws.
Notes: Values in columns 2-5 are monthly. The median household income is median income among renter households in each state. The potential UI benefit is the minimum value of either half the value of the monthly median household income or the state's monthly maximum benefit. The state's monthly maximum benefit is calculated by multiplying 4.33 to the state's maximum weekly benefit amount values (Table 2, Column 3). The maximum duration is the state's maximum duration in weeks. The maximum coverage is calculated by dividing 52 (the number of weeks in a year) by the maximum duration values (Table 2, Column 6).

Renters who have lost their job may be concerned not just about the amount of benefits they receive, but also the length of time they receive them. Column 6 calculates the potential impact of UI on renters through the maximum months of coverage that maximum benefit duration provides. Most states provide 6 months of coverage. Massachusetts provides the most coverage, nearly 7 months (30 weeks), while Florida provides the least coverage, under 3 months (12 weeks). If UI benefits do not aid in eviction prevention, it may be that UI does not replace enough of workers' lost wages or does not provide a long enough duration of benefits.

Extended Benefits. Extended UI benefits can affect regular UI benefits in amount or duration. The two extended benefit programs that are of interest to this paper are the Emergency Unemployment Compensation (EUC) program and the Extended Benefits (EB) program. Both these programs affected regular UI benefits by extending benefit duration at some point from 2002-2016. However, length of extensions differed by program and by the level of unemployment in a given state.

The EUC program was enacted in June 2008 and ran thru December 2013. It provided several extensions to the duration of unemployment benefits, which were determined by levels of unemployment in the state. At its peak, the EU program provided four tiers worth of extensions, providing up to 53 additional weeks of benefits for some states. The EB program, which is permanent, was adopted in 1970. This program provides a mandated extension of duration when the state's unemployment rate reaches certain levels. However, states can opt for additional triggers that are considered easier to reach. Prior to the Great Recession only a few states opted into these triggers. Usually, fifty percent of the EB program is paid for by the Federal government and fifty percent by the states, but during and after the Great Recession, from 2008 to 2013, the federal government completely paid for the EB program. As a result, a few states elected to use the optional easier triggers during the period the Federal government completely covered the cost.

Although extended benefits may affect filings, this paper focuses only on the effects of regular UI benefits, because they are consistently available throughout the time period. Additionally, these are the first benefits an individual receives, even when extensions are in effect. My empirical work does control for the presence of extended benefits, but it does not discuss the effect of these benefits in depth. As a robustness check, I evaluate the impact of UI benefit generosity on eviction filing rates using a measure that incorporates extended benefits.

Theoretical Model

In Chapter III, I developed a theoretical model that I will adapt here to provide insight into the expected effect of UI benefits on eviction filings. Let *r* be the county-level unemployment rate, *b* be the state-level UI benefits, and *c* be the landlord's cost of an eviction filing. I write the theoretical model for county-level eviction filing rate, e, as follows:

$$e = (r(1-b))\left(\frac{1}{2} - cr(1-b)\right)$$

Recall from Chapter III that both partial derivatives and the cross partial could be either positive or negative depending on the levels of *r*, *b*, or *c*. This has important implications for the research question in this chapter. The model suggests that there is no straightforward effect of UI benefits on mitigating the effect of unemployment on eviction. The eviction filing rate may increase or decrease depending on the combination of county-level unemployment, state-level benefits, and costs of eviction.

Data

Data and Variables

Evictions. To capture eviction outcomes, I use the county-level *eviction filing rate* from 2002 to 2016 from the Eviction Lab. I choose to exclude the 2000 and 2001 data, because more counties have missing data in those years than in the rest of the data. The eviction filing rate is the number of eviction filings in a county (which may include multiple filings against the same household) divided by the number of renter-occupied households in the county multiplied by 100. As a result, the *eviction filing rate* can be interpreted as the number of eviction filings per 100 renter-occupied households.

UI Benefits. Data for state UI policies come from Hsu et al. (2018b) and the US Department of Labor Employment & Training Administration. Hsu et al. (2018b) is the publicly available dataset for Hsu et al. (2018a). The authors collected maximum weekly benefits and maximum benefit duration for each state from the Significant Provisions of State Unemployment Insurance Laws. These documents track the minimum and maximum benefits awarded in each state, as well as the durations and qualifications in each state. I use their data from 2002 to 2010. I complete the dataset by obtaining data for 2011 to 2016, following the same process as Hsu et al. (2018a). I use maximum weekly benefits and maximum benefit duration in each state from the January publication of the Significant Provisions of State UI Laws for 2011 to 2016 (Department of Labor, 2011-2016).

To capture each state's UI policy, I follow Hsu et al. (2018a) by focusing on each state's UI generosity. Like Hsu et al. (2018a), I construct *maximum benefit* from the product of each state's maximum weekly benefit and maximum number of weeks for which benefits are paid (excluding extensions weeks from the EUC and EB programs). *Maximum benefit* captures the generosity of each state's UI policy. It serves as a proxy for the total regular benefits that an unemployment insurance claimant could receive during an unemployment spell (Hsu et al, 2018a). As a sensitivity check, I also consider a number of additional measures of UI generosity to see if the results differ.

For measures of UI extensions, specifically the Extended Benefits (EB) and Extended Unemployment Compensation (EUC) programs, I collect data from the EB and EUC trigger notices provided by the US Department of Labor Employment & Training Administration (https://oui.doleta.gov/unemploy/claims_arch.asp). These trigger notices capture when each state's unemployment rate was high enough to initiate the starting or stopping each of these programs. I collect trigger notices for the last week of December in each year from 2002-2016 for the EB program (the duration available, as the EB program is permanent) and from 2008-2013 for the EUC program (the duration available, as the EUC program was temporary).

I capture extended benefits as a separate control. I construct *extended benefits*, which is the product of each state's maximum weekly benefit and number of extension weeks for which benefits are paid. I calculate the number of extension weeks from the EUC and EB trigger notices from the last week of December in each year. I assume that the maximum number of extension weeks available during this week is the number of extension weeks available during the entire year. I combine the maximum number of extension weeks for each program to yield the total number of extension weeks for which benefits are paid.

Controls. In the empirical work that follows, I include county-level controls. I collect data on county-level household income, gross rent, rent burden, and race from the Eviction Lab. I pull data on county-level unemployment rates from the Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics (LAUS). The BLS LAUS contains unemployment rates for all counties in the United States across time. I use the county-level unemployment rates from 2002 to 2016. The BLS LAUS is the most comprehensive data on unemployment at the county-level making it the best choice for this research. Lastly, I define counties as urban or rural using the rural-urban continuum codes from the U.S. Department of Agriculture, Economic Research Service (USDA ERS, 2004; USDA ERS, 2013).

I also include controls for state-level economic conditions that may affect county-level eviction filing rates. I include a measure of real GDP per capita, which I take from the Bureau of Economic Analysis from 2002-2016; the Housing Price Index (HPI), which I obtain from the Federal Housing Finance Agency; the state-level unemployment rate, which I collect from the BLS LAUS; and state annual wages from the BLS, Quarterly Census of Employment and Wages.

Descriptive Statistics

The final data set used in this paper is an unbalanced county-level panel dataset containing 39,369 observations from 2,924 US counties from 2002-2016. The dataset includes all continental US counties except for DC and Maryland. DC has been excluded because it is not a county or a state making it difficult to include in the analysis. Maryland is excluded because it has a significantly different way of counting its eviction filings, which makes its data difficult to compare to other states.

Means and standard deviations for all variables are presented in Table 7.4. The first part of the table describes the state-level data, while the second half of the table describes the county-level data. The average maximum regular benefit is $10,650 with a standard deviation of $381. Note that the variation in the maximum benefit is primarily driven by the variation in maximum weekly benefit, as opposed to maximum duration. There is much more variability across states and time in benefit amounts than in the number of weeks those benefits are paid out. Turning to the county-level data, the average eviction filing rate is 3.1 with a standard deviation of 4.78.

Table 7.4 Summary Statistics

	Mean	Median	SD
Panel A. State characteristics (2002-2016, N = 705)			
Unemployment insurance			
Max Benefit ($ thousands)	10.65	10.19	3.81
Max Weekly Benefit ($ thousands)	0.41	0.39	0.13
Max Regular Duration (weeks)	25.77	26.00	1.89
Real Maximum UI Benefit	12.01	11.58	4.11
Average Weekly Benefit ($ thousands)	0.29	0.28	0.05
Adjusted Max Benefit ($ thousands)	18.79	12.99	13.99
Economic variables			
Unemployment rate (%)	6.02	5.60	2.01
log of real GDP per capita	10.78	10.76	0.18
Home price growth (%)	2.29	2.35	5.96
Average annual wages ($ thousands)	41.94	40.97	8.03
Panel B. County characteristics (2002-2016, N = 39,369)			
Eviction and housing			

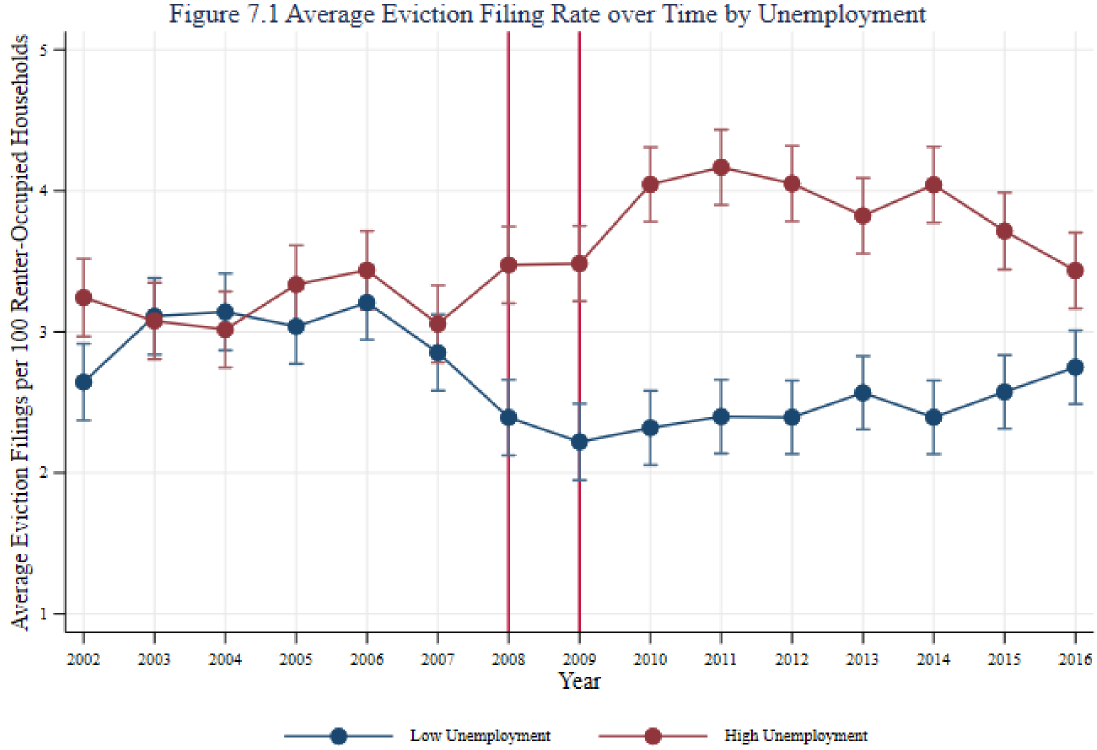
Eviction filing rate	3.10	1.54	4.78
Employment, income, and rent			
Unemployment rate (%)	6.50	5.90	2.72
log of median household income	10.75	10.75	0.24
Median gross rent ($ hundreds)	6.76	6.41	1.87
Median rent burden	27.10	27.20	4.79
Demographics			
African American (%)	8.37	1.72	14.06
Hispanic (%)	7.68	2.83	12.80
Urban	0.34	0.00	0.47

Notes: This table describes my main sample. Max Benefit, Max Weekly Benefit, Average Weekly Benefit, and Adjusted Max Benefit are not adjusted for inflation. Home price growth is captured by the percent change in the Housing Price Index. Average annual wages capture the average state-level wage.

Descriptive Analysis

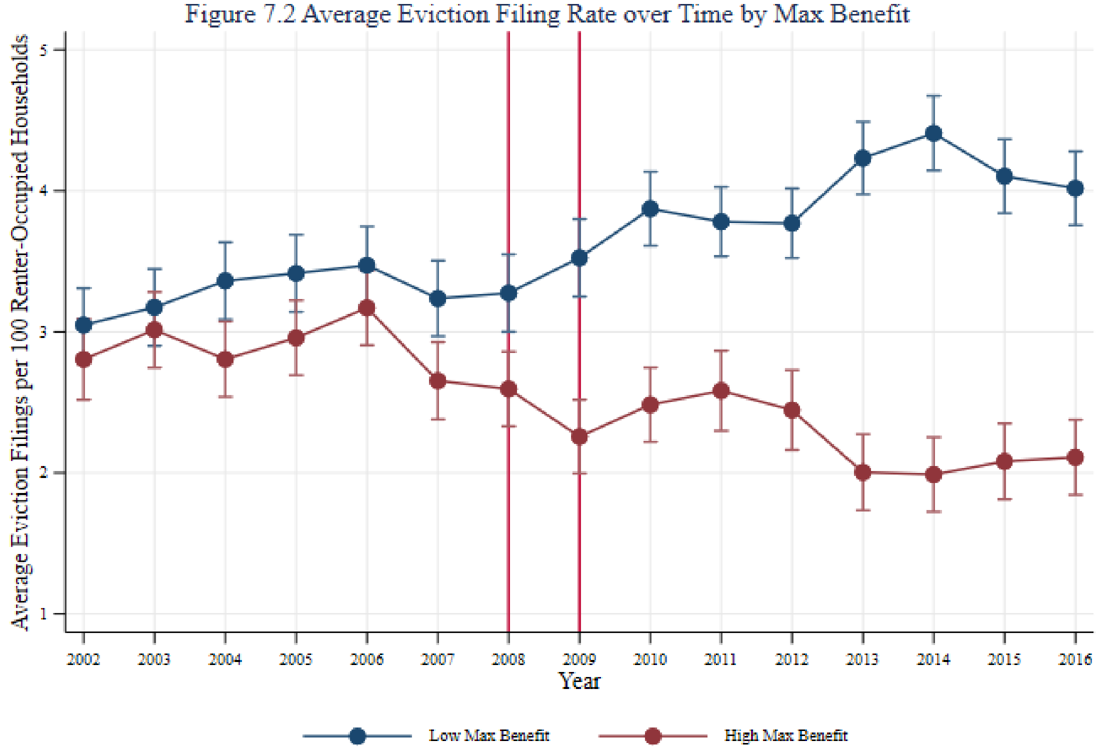
If UI benefits prevent eviction filings, it is likely by mitigating a negative effect of unemployment on eviction filings. I begin by exploring the relationship between unemployment rates and eviction filing rates graphically. *Unemployment Rate* is a continuous variable, which is difficult to capture in a simple graphical analysis, so I use it to construct two groups: *Low Unemployment Rate* and *High Unemployment Rate*. For each year of data, I group counties by comparing their unemployment rate to the median unemployment rate. If a county's *Unemployment Rate* is less than the median in a given year, the county is considered a *Low Unemployment Rate* county in that year. If a county's *Unemployment Rate* is greater than or equal to the median in a given year, the county is considered a *High Unemployment Rate* county in that year. In Figure 7.1, I plot the average eviction filing rate over time by *Unemployment Rate* groups. It shows that the average eviction filing rate among counties with high unemployment rates tends to be higher than the average eviction filing rate among counties with low unemployment rates. In most years prior to 2007, the means are not statistically different. In 2007, the means begin to diverge and by 2008, the means are statistically different. Although the gap begins to close around 2014, the means remain statistically different between the two groups through 2016. This suggests that the relationship between unemployment and eviction filings may differ over time.

Figure 7.1 Average Eviction Filing Rate over Time by Unemployment



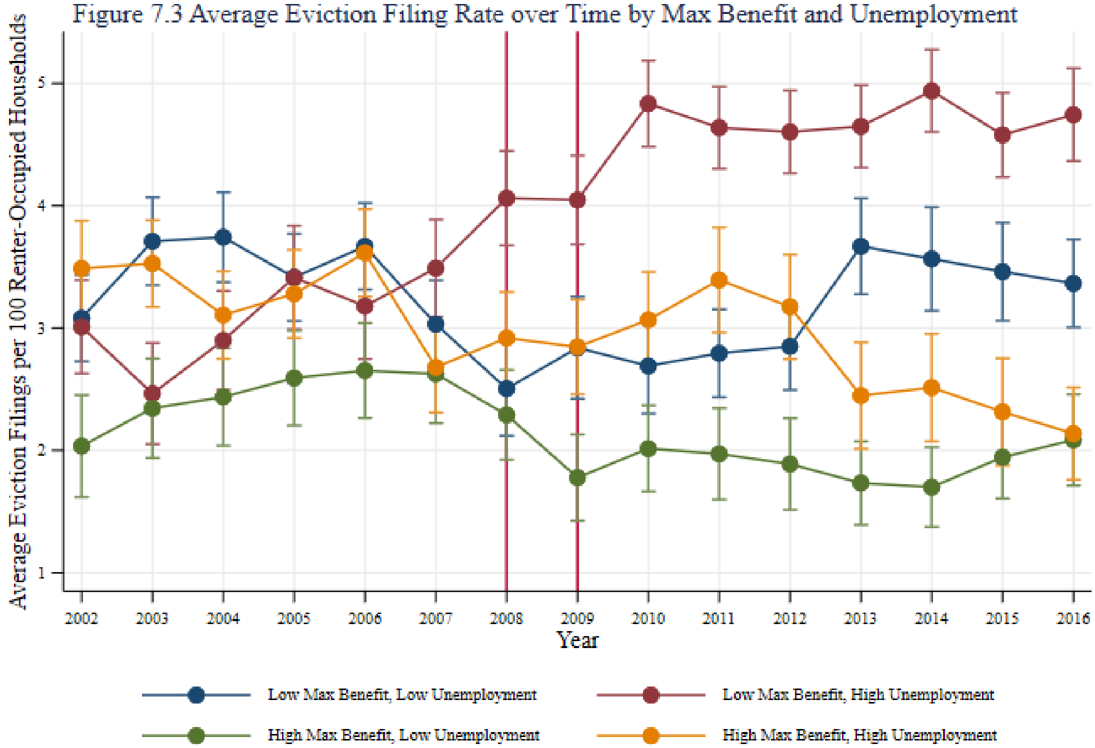
Next, I explore the relationship between UI benefits and eviction filing rates graphically. Like *Unemployment Rate*, *Max Benefit* is a continuous variable, so I use it to construct two groups: *Low Max Benefit* and *High Max Benefit*. Again, I group counties by comparing their UI benefits to the median UI benefit. If a county's *Max Benefit* is less than the median in a given year, the county is considered a *Low Max Benefit* county in that year. If a county's Max Benefit is greater than or equal to the median in a given year, the county is considered a *High Max Benefit* county in that year. In Figure 7.2, I plot the average eviction filing rate over time by *Max Benefit* groups. It shows that the average eviction filing rate among counties with low benefits tends to be higher than the average eviction filing rate among counties with high benefits. In most years prior to 2007, the means are not statistically different. In 2007, the means begin to diverge and by 2008, the means are statistically different. They remain so through 2016. Figure 7.2 suggests there may not have been an effect of regular UI benefits on eviction filing rates prior to the Great Recession, but higher UI benefits may have helped eviction filing rates remain low during and after the Great Recession.

Figure 7.2 Average Eviction Filing Rate over Time by Max Benefit



Lastly, I combine the two previous figures to explore the potential mitigating effect of UI benefits on unemployment rates. When benefits are low, a change from low to high unemployment may increase the average eviction filing rate, because low benefits can do little to mitigate the potential negative effect of unemployment. However, when benefits are high, a change from low to high unemployment may not increase the average eviction filing rate, because high benefits mitigate the negative effect of unemployment. In Figure 7.3, I plot the average eviction filing rate over time by unemployment and UI benefits.

Figure 7.3 Average Eviction Filing Rate over Time by Max Benefit and Unemployment



Prior to the Great Recession, the average eviction filing rate across groups is relatively consistent. In 2008, the averages begin to diverge. The low benefit, high unemployment rate group begins to see a significantly higher average eviction filing rate than the other three groups. This pattern remains even after the Great Recession. In 2009, the average eviction filing rate for the other three groups begins to diverge. The high benefit, low unemployment rate group now has a significantly lower average eviction filing rate. Both the low benefit, high unemployment rate group and the high benefit, low unemployment rate group have similar average eviction filing rates, until 2013, when the average for the high benefit, high unemployment rate group becomes significantly smaller.

The graph suggests that UI benefits may be able to mitigate a negative effect of unemployment during and after the Great Recession. When benefits are low, a change from low to high unemployment increases the average eviction filing rate significantly, which suggests that low benefits can do little to mitigate the negative effect of unemployment. However, when benefits are high, a change from low to high unemployment does not always increase the average eviction filing rate significantly, which suggests that high benefits mitigate the negative effect of unemployment.

Methodology

The graphical relationships are revealing, but the simple plots over time do not control for other county or state characteristics. To account for such factors, I turn to regression analysis. In developing my estimation equation, I use Figures 7.1-7.3 as a guide. Figures 7.1 and 7.2 suggest that I allow for the possibility of different effects of unemployment rates and UI benefit generosity before, during, and after the Great Recession. During the Great Recession unemployment uptake and duration increased (BLS, 2020; Kroft et al., 2016). Additionally, the characteristics of the unemployed changed (Mattingly et al., 2011). Unemployment rates amongst single mothers and those living in urban areas increased significantly (Mattingly et al., 2011). Both groups are especially prone to eviction. Figure 7.3 suggests that I allow for the possibility of different effects of unemployment rates at different levels of UI benefits. Research shows that the marginal person transitioning into unemployment differs when the unemployment rate is low than when it is high (Ahn and Hamilton, 2020). Taken together, the figures, as well as economic research, suggest the inclusion of interaction terms.

I am interested in how UI benefit generosity affects the impact of county-level unemployment on county-level eviction filing rates. Specifically, I am interested in whether higher UI benefit generosity can mitigate a negative effect of involuntary unemployment on eviction filings. To understand how UI benefit generosity affects the impact of unemployment rates on county-level eviction filings rates, I need to isolate the effect of UI benefit generosity. To control for potential confounding factors, I employ a continuous treatment DDD empirical strategy. Although my measures of UI benefit generosity and unemployment are continuous, we can think of me having four groups: (1) higher county-level unemployment rates in states with higher UI benefit generosity, (2) higher county-level unemployment rates in states with lower UI benefit generosity, (3) lower county-level unemployment rates in states with higher UI benefit generosity, and (4) lower county-level unemployment rates in states with lower UI benefit generosity. I compare differences between these four groups in periods during and after the Great Recession to before the Great Recession—which is my third level of differencing—to ask how the impact of involuntary unemployment on eviction filing rates depended on state UI benefit generosity. I chose to consider the recession period itself and the ensuing period separately. This implies that I have two DDD estimators—one pertaining to the Great Recession period relative to the earlier prerecession period, and the other pertaining to the post-Great Recession period relative to the same prerecession period.

My primary method for answering the question of how state-level UI benefit generosity affects county-level eviction filings rates is the following specification. The main estimating equation takes the following form:

$$
\begin{aligned}
EFR_{cst} = \beta_0 &+ \beta_1 Max\ Benefit_{st} + \beta_2 Unemployment\ Rate_{cst} + \beta_3 GR_t + \beta_4 Post\ GR_t \\
&+ \beta_5 Max\ Benefit_{st} \times Unemployment\ Rate_{cst} \\
&+ \beta_6 GR_t \times Max\ Benefit_{st} + \beta_7 GR_t \times Unemployment\ Rate_{cst} \\
&+ \beta_8 GR_t \times Max\ Benefit_{st} \times Unemployment\ Rate_{cst} \\
&+ \beta_9 Post\ GR_t \times Max\ Benefit_{st} \\
&+ \beta_{10} Post\ GR_t \times Unemployment\ Rate_{cst} \\
&+ \beta_{11} Post\ GR_t \times Max\ Benefit_{st} \times Unemployment\ Rate_{cst} + \boldsymbol{\gamma X}_{cst} \\
&+ \boldsymbol{\delta Z}_{st} + \boldsymbol{\lambda}_s + \varepsilon_{cst}
\end{aligned}
$$

The dependent variable, *EFR*, is the eviction filing rate for county, *c*, in state, *s*, and year, *t*. The independent variables are *Max Benefit*, the product of the maximum weekly benefit amount and the maximum benefit duration (in weeks) for state, *s*, in year, *t*; *Unemployment Rate*, the unemployment rate for county, *c*, in year, *t*; *GR*, a dummy variable indicating that the year, *t*, is during 2008 or 2009; and *Post GR*, a dummy variable indicating that the year, *t*, is after 2010. **X** is a vector of county characteristics; **Z** is a vector of time-variant state characteristics; **λ** represents a vector of state fixed effects; and *ε* is the error term. *Max Benefit* and *Unemployment Rate* are demeaned (with respect to the mean for the entire sample) before they are interacted, so β_5 measures the change in the county-level eviction filing rate associated with the average county-level unemployment rate in a state with average UI generosity before the Great Recession. β_8 and β_{11} measure this change during and after the Great Recession, respectively. The vector **X** includes median household earnings, median gross rent, median rent burden, percent African American, percent Hispanic, and a dummy variable equal to 1 if the county is urban and 0 otherwise. The vector **Z** includes the following state-level economic conditions: the state unemployment rate, log of real GDP per capita, home price growth, average wages, and maximum UI benefit extensions. The main results reported in Table 6 are ordinary least squares estimates of the fixed effects model with standard errors adjusted for clustering at the state level.

Determining a causal effect of UI benefit generosity on eviction filing rates relies on the assumption that differences in UI benefit generosity are not correlated with other factors that affect changes in eviction filing rates. This assumption seems plausible as UI benefit generosity is captured at the state-level, while eviction filing rates are captured at the county-level. Eviction filing rates are determined locally, but individual local factors should not influence state-level policy choices.

A concern could be that state legislators change UI generosity in response to economic shocks, which may be determinants of county-level eviction filing rates and could confound my estimates. To address this concern, I follow Hsu et al. (2018a) and estimate the correlation of benefit levels with various state macroeconomic variables, conditional on state fixed effects. Unlike Hsu et al. (2018a), the results, which are reported in columns 1-4 of Table 7.5, show evidence of a relation. Individually, I estimate a positive, statistically significant relationship between UI benefits and real GDP per capita, we well as between UI benefits and state wages. When estimating the correlation of benefits levels with all state macroeconomic variables, I find a positive, statistically significant relationship between UI benefits and the state unemployment rate, as well as between UI benefits and real GDP per capita. This difference may be due to differing time periods because my analysis extends to 2016, whereas previous research has stopped around 2010. To account for the resulting endogeneity, I include these variables in my main estimating equation. As a robustness check, I estimate the model with state-by-year fixed effects.

Table 7.5 Regressions of Maximum UI Benefit on Economic Variables

	Maximum UI Benefit				
	(1)	(2)	(3)	(4)	(5)
Unemployment Rate	-0.0132				0.249**
	(0.084)				(0.109)
Real GDP per Capita		8.993***			8.055***
		(1.915)			(2.839)
Housing Price Index			-0.0144		-0.00555
			(0.014)		(0.015)

Wages				0.358***	0.187
				(0.101)	(0.122)
Observations	705	705	705	705	705
R^2	0.9205	0.9315	0.9207	0.9316	0.9361

Notes: Clustered standard errors in parentheses. Clustering at the state-level. Each model includes state and year fixed effects. Maximum UI Benefit captured in real terms.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Results

Discrete Results

I begin by estimating a simple model that only includes discrete measures of *Unemployment Rate* and *Max Benefit*, as well as *GR*, and *Post GR*. In terms of the main estimating equation presented in Section 5, this simple model excludes all interaction terms. As reported in column 1 of Table 7.6, the coefficient of *High Unemployment* is negative and statistically significant. The estimate of 0.379 suggests that a county in the high unemployment rate group is associated with 0.379 less eviction filings per 100 renter-occupied households than a county in the low unemployment rate group. As reported in column 1 of Table 7.6, the coefficient of *High Max Benefit* is positive. The coefficients on *GR* and *Post GR* show that, on average, eviction filing rates increased during and after the Great Recession.

To determine whether there is a mitigating effect of UI benefits on unemployment, I estimate the same simple model with the inclusion of one interaction term, *Unemployment Rate* × *Max Benefit*. These estimates are reported in column 2 of Table 7.6. The coefficient on the *High Unemployment* × *High Max Benefit* interaction is positive and statistically significant. The coefficient of 0.503 suggests that the marginal effect of *High Unemployment* increases by 0.503 eviction filings per 100 renter-occupied households for counties in the high maximum benefit group. This suggests that, instead of mitigating the effect of the unemployment rate, benefits reinforce the effect.

Table 7.6.
The Effect of UI Generosity on Eviction Filing Rates, 2002-2016

	(1)	(2)	(3)
High Max Benefit	0.142	-0.0896	-0.186
	(0.192)	(0.206)	(0.237)
High Unemployment	-0.379**	-0.624***	-0.658**
	(0.173)	(0.231)	(0.281)
Great Recession	0.0148	0.0393	-0.197
	(0.157)	(0.159)	(0.353)
Post Great Recession	0.261	0.289	0.314
	(0.221)	(0.222)	(0.241)
High Max Benefit # High Unemployment		0.503*	0.708*
		(0.290)	(0.377)
High Max Benefit # Great Recession			0.425
			(0.445)
High Max Benefit # Post Great Recession			0.0493
			(0.194)
High Unemployment # Great Recession			0.271
			(0.396)
High Unemployment # Post Great Recession			-0.00291
			(0.235)
High Max Benefit # High Unemployment # Great Recession			-0.531
			(0.416)
High Max Benefit # High Unemployment # Post Great Recession			-0.296
			(0.312)
Constant	-22.46*	-22.95*	-22.87*
	(12.363)	(11.602)	(11.916)
Observations	39391	39391	39391
R^2	0.3825	0.3830	0.3832

The graphical analysis in Descriptive Analysis section suggested that the effect of unemployment on filings, as well as unemployment on filings by benefits, may differ by time period, namely during and after the Great Recession. To assess how the interaction between benefits and unemployment differs across time periods, I interact the *High Unemployment* × *High Max Benefit* interaction with the period indicator variables. As reported by column 3 in Table 7.6, the coefficient on *High Max Benefit* is negative and statistically different from zero. The coefficient on the *High Unemployment* × *High Max Benefit* interaction is positive and statistically significant. Taken together, the coefficients on *High Max Benefit* and *High Unemployment* × *High Max Benefit* capture the effect of benefit generosity on eviction filings before the Great Recession.

I find that the interaction between benefits and unemployment differs by time period. The coefficients on the *Great Recession* × *High Unemployment* × *High Max Benefit* interaction and the *Post Great Recession* × *High Unemployment* × *High Max Benefit* interaction are both negative and statistically significantly different from zero. These interaction terms suggest that the positive interaction effect is mitigated during and after the Great Recession.

Continuous Results

Next, I begin by estimating a simple model that only includes *Unemployment Rate*, *Max Benefit*, *GR*, and *Post GR*. In terms of the main estimating equation presented in Section 5, this simple model excludes all interactions terms. In this specification, the coefficient on *Unemployment Rate* measures the average association between unemployment rates and eviction filing rates. As reported in column 1 of Table 7.7, the estimate is positive. The coefficient on *Max Benefit* measures the average association between maximum benefit generosity and eviction filing rates. As reported in column 1 of Table 7.7, the estimate is positive and statistically significant. The coefficient of 0.148 suggests that a $1,000 increase in state-level maximum UI benefit generosity leads to a 0.148 increase in county-level eviction filings per 100 renter-occupied households. The coefficients on *GR* and *Post GR* show that, on average, eviction filing rates increased during and after the Great Recession.

To determine whether there is a mitigating effect of UI benefits on unemployment, I estimate the same simple model with the inclusion of one interaction term, *Unemployment Rate* × *Max Benefit*. These estimates are reported in column 2 of Table 6. Recall that both *Unemployment Rate* and *Max Benefit* are demeaned, so the coefficient on *Unemployment Rate* measures the change in the average county-level eviction filing rate for a change in the unemployment rate at the mean maximum UI benefit generosity. The coefficient on the *Unemployment Rate* × *Max Benefit* interaction is positive and statistically significant. The coefficient of 0.0435 suggests that the marginal effect of *Unemployment Rate* increases by 0.0435 eviction filings per 100 renter-occupied households for every $1,000 increase in maximum UI benefit generosity. This suggests that, instead of mitigating the effect of the unemployment rate, benefits reinforce the effect.

Thus far, I have examined unemployment and benefits to gauge the average effect of benefit generosity on filing rates. However, the graphical analysis in Section 4 suggested that the effect of unemployment on filings, as well as unemployment on filings by benefits, may differ by time period, namely during and after the Great Recession. To assess how the interaction between benefits and unemployment differs across time periods, I interact the *Unemployment Rate* × *Max Benefit* interaction with the period indicator variables. As reported by Column 3 in Table 6, the coefficient on *Max Benefit* remains positive and statistically different from zero. The coefficient on the *Unemployment Rate* × *Max Benefit* interaction is positive and statistically significant. Taken together, the coefficients on *Max Benefit* and *Unemployment Rate* × *Max Benefit* capture the effect of benefit generosity on eviction filings before the Great Recession.

I find that the interaction between benefits and unemployment differs by time period. The coefficients on the *Great Recession* × *Unemployment Rate* × *Max Benefit* interaction and the

Post Great Recession × *Unemployment Rate* × *Max Benefit* interaction are both negative and statistically significantly different from zero. These interaction terms suggest that the positive interaction effect is mitigated during and after the Great Recession.

Table 7.7 The Effect of Max UI Benefit on Eviction Filing Rates, 2002-2016

	Eviction Filing Rate		
	(1)	(2)	(3)
Max UI Benefit	0.148***	0.164***	0.296***
	(0.034)	(0.031)	(0.073)
Unemployment Rate	0.0191	0.0236	0.148
	(0.060)	(0.060)	(0.108)
Great Recession (GR)	0.524**	0.766***	0.426*
	(0.213)	(0.235)	(0.228)
Post Great Recession (Post GR)	0.689**	0.860***	0.534*
	(0.274)	(0.283)	(0.284)
Max UI Benefit × Unemployment Rate		0.0435***	0.113***
		(0.010)	(0.028)
GR × Max UI Benefit			-0.109*
			(0.064)
GR × Unemployment Rate			-0.137*
			(0.076)
GR × Max UI Benefit × Unemployment Rate			-0.0646**
			(0.025)
Post GR × Max UI Benefit			-0.140**
			(0.061)
Post GR × Unemployment Rate			-0.142*
			(0.073)
Post GR × Max UI Benefit × Unemployment Rate			-0.0745***
			(0.028)
County controls	Yes	Yes	Yes
State controls	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes
Observations	39369	39369	39369

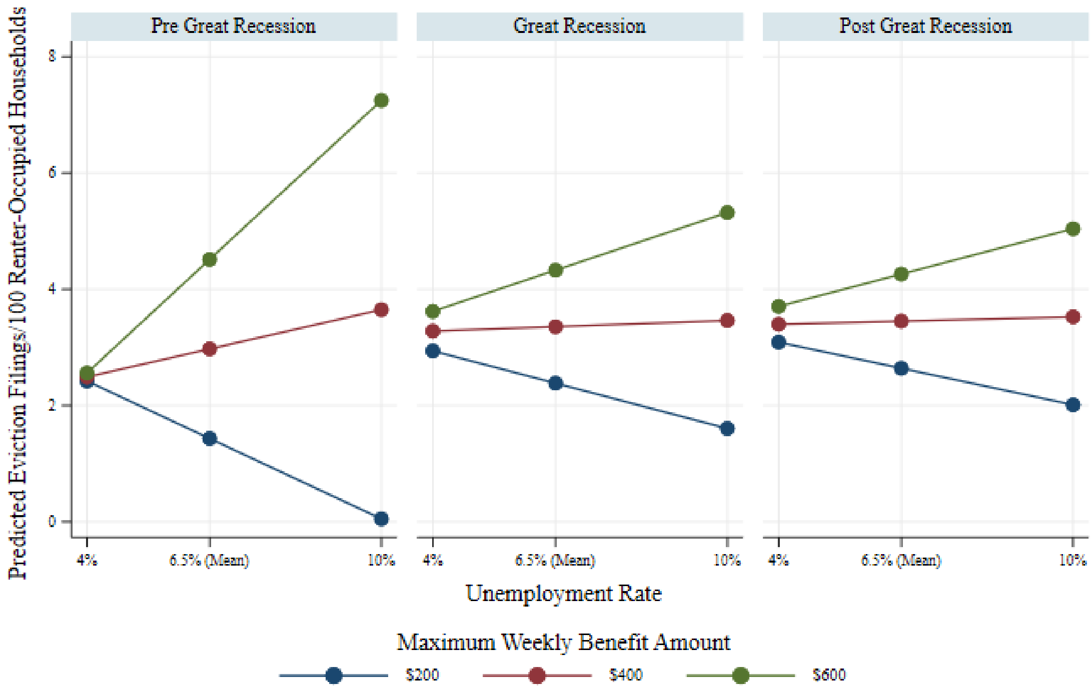
R^2	0.5179	0.5206	0.5221

Notes: Clustered standard errors in parentheses. Clustering at the state-level. County controls include median household income, median gross rent, median rent burden, percent African American, and percent Hispanic. State controls include extended benefits, unemployment rate, real GDP, HPI, and average annual wage. Significance is * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The coefficients on the interaction terms are difficult to interpret. To ease interpretation, in Figure 7.4, I plot the expected eviction filings per 100 renter-occupied households at different values of benefits and unemployment rates in each time period. Each line captures a different level of unemployment. For ease of interpretation, benefits are measured as weekly benefits for 26 weeks duration. In terms of maximum benefits used in the model \$200, \$400, and \$600 are equivalent to \$5,200, \$10,400, and \$15,600, respectively. The x-axis captures values of unemployment, namely full employment (4%), mean unemployment (6.5%), and high unemployment (10%). All of these are values of unemployment rates observed in my sample. Moving along a given line shows the effect of an increase in unemployment rate on expected eviction filings.

As shown, prior to the Great Recession, at low unemployment, there is a negative effect of increasing unemployment on predicted eviction filings. However, as benefits increase, the effect of unemployment on filings becomes positive. During and after the Great Recession, the overall effects are less extreme. The effect of increasing unemployment on predicted filings remains negative for low benefits during and after the Great Recession. As benefits increase, the effect of unemployment on predicted eviction filings again become positive. However, it is not as strong of relationship as that before the Great Recession.

Figure 7.4 Predictive Margins
The Effect of UI Benefits on Eviction Filing Rates



Robustness

The results presented in column 3 of Table 7.7 are robust to a number of changes in specification. The results of these alternative specifications are presented in Tables 7.8 and 7.9. In column 1 of Table 7.8, 1 examine the robustness of the model to the use of real values instead of nominal. Results remain unchanged. In columns 2-4, I estimate the model without state-level controls, with county fixed effects, and with state-by-year fixed effects, respectively. Results are consistent with those in the primary specification. The robustness to state-by-year fixed effects is noteworthy, because it eliminates our earlier concern about economic shocks.

Table 7.8
Robustness of Model to Changes to Real Values and Changes in Fixed Effects

	Eviction Filing Rate			
	Real Values (1)	Drop State Controls (2)	County FE (3)	State-by-year FE (4)
Max UI Benefit	0.299***	0.194*	0.185***	
	(0.071)	(0.103)	(0.057)	
Unemployment Rate	0.0640	0.223**	-0.00480	0.195*
	(0.095)	(0.110)	(0.026)	(0.105)
Max UI Benefit × Unemployment Rate	0.0967***	0.123***	0.0191**	0.128***
	(0.027)	(0.031)	(0.008)	(0.031)
Great Recession (GR)	0.166	-1.085***	-0.0462	
	(0.180)	(0.357)	(0.119)	
Post Great Recession (Post GR)	-0.0145	-1.586***	0.170	
	(0.187)	(0.487)	(0.179)	
GR × Max UI Benefit	-0.0994	-0.162**	-0.0378	
	(0.061)	(0.072)	(0.040)	
GR × Unemployment Rate	-0.0807	-0.254**	-0.0172	-0.222***
	(0.061)	(0.107)	(0.034)	(0.074)
GR × Max UI Benefit × Unemployment Rate	-0.0528**	-0.0842***	-0.0203**	-0.0466**
	(0.025)	(0.028)	(0.009)	(0.023)
Post GR × Max UI Benefit	-0.127**	-0.146*	-0.0577	
	(0.057)	(0.073)	(0.038)	
Post GR × Unemployment Rate	-0.0398	-0.203**	0.00641	-0.190***
	(0.059)	(0.091)	(0.031)	(0.067)
Post GR × Max UI Benefit × Unemployment Rate	-0.0581**	-0.0934***	-0.0242**	-0.0481
	(0.027)	(0.030)	(0.010)	(0.029)
County controls	Yes	Yes	Yes	Yes
County fixed effect	No	No	Yes	No
State controls	Yes	No	Yes	No
State fixed effects	Yes	Yes	No	No
State-by-year fixed effects	No	No	No	Yes

Observations	39369	39369	39369	39369
R^2	0.523	0.517	0.926	0.542

Notes: Column 1 presents results from the primary specification with real, instead of nominal, values for benefits, median household income, and median gross rent. Column 2 presents results from the primary specification without state-level controls. Column 3 presents results from the primary specification with county fixed effects. Column 4 presents results from the primary specification with state-by-year fixed effects. Clustered standard errors in parentheses. Clustering at the state-level. County controls include median household income, median gross rent, median rent burden, percent African American, and percent Hispanic. State controls include extended benefits, unemployment rate, real GDP, HPI, and average annual wage. Significance is * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In columns 1-3 of Table 7.9, I estimate the model using different measures of UI benefit generosity. In column 1, I use maximum weekly benefit, in column 2, maximum duration, and in column 3, average weekly benefit amount paid. These results are relatively consistent with those in the primary specification. All but maximum benefit duration suggest a positive relationship between benefits and filings. All three suggest that the effect is reinforced by unemployment rates and mitigated over time. Finally, in 4olumn 4 of Table 7.9, I weight the primary model by county population. The main conclusion of a positive relationship between benefits and filings, which is reinforced by unemployment hold. However, in this model, that relationship does not appear to change over time.

Table 7.9 Robustness of Model to Changes in Max UI Benefit and Addition of Weights

	Eviction Filing Rate			
	WBA (1)	Duration (2)	AWBA (3)	Weighted (4)
Max UI Benefit	0.00922^{***}	-0.0151	0.0138^{**}	0.419^{*}
	(0.002)	(0.057)	(0.005)	(0.234
Unemployment Rate	0.186	-0.00813	0.167	0.341
	(0.114)	(0.103)	(0.129)	(0.207)
Max UI Benefit × Unemployment Rate	0.00329^{***}	0.0958^{**}	0.00472^{**}	0.105^{*}
	(0.001)	(0.037)	(0.002)	(0.055)
Great Recession (GR)	0.332	0.487^{**}	0.246	0.117
	(0.229)	(0.209)	(0.273)	(0.485)

Post Great Recession (Post GR)	0.409	0.642**	0.404	0.450
	(0.288)	(0.287)	(0.347)	(0.697)
GR × Max UI Benefit	-0.00345*	0.0620	-0.00564	-0.139
	(0.002)	(0.095)	(0.004)	(0.117)
GR × Unemployment Rate	-0.169**	0.00133	-0.173*	-0.131
	(0.080)	(0.072)	(0.097)	(0.158)
GR × Max UI Benefit × Unemployment Rate	-0.0020***	-0.0459	-0.00254*	-0.0740
	(0.001)	(0.050)	(0.001)	(0.047)
Post GR × Max UI Benefit	-0.0042**	0.0969	-0.00502	-0.149
	(0.002)	(0.072)	(0.004)	(0.127)
Post GR × Unemployment Rate	-0.184**	0.0230	-0.162*	-0.0960
	(0.080)	(0.066)	(0.093)	(0.163)
Post GR × Max UI Benefit × Unemployment Rate	-0.0023***	-0.0717**	-0.0031**	-0.0778
	(0.001)	(0.035)	(0.001)	(0.049)
County controls	Yes	Yes	Yes	Yes
State controls	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Observations	39369	39369	39311	39369
R^2	0.522	0.518	0.520	0.653

Notes: Column 1 uses maximum weekly benefit amount (WBA) as the measure of UI benefit generosity. Column 2 uses maximum benefit duration as the measure of UI benefit generosity. Column 3 uses average weekly benefit amount (AWBA) as the measure of UI benefit generosity. Column 4 weights the primary specification by county population. Clustered standard errors in parentheses. Clustering at the state-level. County controls include median household income, median gross rent, median rent burden, percent African American, and percent Hispanic. State controls include extended benefits, unemployment rate, real GDP, HPI, and average annual wage. Significance is * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Discussion

My results show a robust, positive effect of the interaction between benefits and unemployment, which decreases slightly during and after the Great Recession. The consistently positive relationship appears counterintuitive. UI benefits are a source of income that could be used to pay rent, so an increase in benefits could make it easier for individuals or families to make their rental payments, especially during times of high unemployment. We would expect, or at least hope, that an increase in UI benefits would lead to a decrease in eviction filings as the unemployment rate increases. That is, we would expect the interaction term to be negative. Furthermore, the graphical analysis supported this hypothesis. My results suggest the opposite, which warrants further discussion.

First, it is important to understand why the graphical analysis and the empirical results tell different stories. The graphical analysis plotted averages over time. It did not account for other county or state characteristics. Once those characteristics are accounted for, the relationship changed. An important factor that the graphs do not account for is state fixed effects. Because my data is counties that are within states, with a state-level policy, it is important to control for fixed effects. Once these fixed effects are included the relationship changes. See Appendix A for more details.

Table 7.10 presents the adjusted predictions of county-level eviction filings per 100 renter-occupied households at representative values of benefits and unemployment before, during, and after the Great Recession. I choose the same levels of benefits and unemployment I plotted in Figure 7.4. All of the controls have been set to their means. The table depicts the consistently positive relationship between benefits and filings. Holding unemployment constant, as we increase UI benefit generosity, we see an increase in the expected county-level eviction filings per 100 renter-occupied households. However, the predicted values are quite small across the entire table.

Additionally, Table 7.10 depicts that the relationship between unemployment and filings varies by benefits. When benefits are low, as we increase unemployment, we see a decrease in the expected county-level eviction filings per 100 renter-occupied households. This negative relationship holds across all time periods. However, the predicted values remain quite small across the entire table. When benefits are average, as we increase unemployment, we increase the eviction filing rate. This relationship also holds across all time periods. Finally, when benefits are large, as we increase unemployment, we increase the eviction filing rate even more.

Table 7.10
Expected County-Level Eviction Filings by UI Benefits and Unemployment Rates

			Expected Eviction Filings		
Weekly Benefit	Maximum Benefit	Unemployment Rate	Pre-Great Recession	During Great Recession	Post-Great Recession
\$200	\$5,200	4%	2.42	2.94	3.09
\$200	\$5,200	6.5%	1.43	2.39	2.64
\$200	\$5,200	10%	0.05	1.61	2.01
\$400	\$10,400	4%	2.49	3.28	3.40
\$400	\$10,400	6.5%	2.97	3.36	3.45
\$400	\$10,400	10%	3.65	3.46	3.53
\$600	\$15,600	4%	2.56	3.62	3.71
\$600	\$15,600	6.5%	4.51	4.33	4.26
\$600	\$15,600	10%	7.25	5.32	5.04

Notes: This table shows the expected eviction filings per 100 renter-occupied households at the county-level from the primary regression results.

Taken together, these results seem to suggest a small change in the number of county-level eviction filings. However, these small county-level effects can result in larger state-level effects once aggregated. For example, using the estimates from the main model, increases the maximum UI benefit generosity by \$1,000, we would expect to see 0.296 more eviction filings per 100 renter-occupied households at the mean level of unemployment. Using North Carolina, where I attended undergraduate and graduate school, as an example, in 2016, the Eviction Lab database estimates that there were over 1.3 million renter-occupied households. Assuming this number, an increase in maximum UI benefits generosity by \$1,000 in North Carolina could result in 3,848 more eviction filings in a given year with average unemployment. If we expect about 40 percent of those filings to result in judgments, then this increase in benefits could lead to nearly 1,540 eviction judgments across the state. According to my calculations using data from the Eviction Lab, in an average year, the number of eviction filings is nearly 150,000. This increase in benefits could lead to around a 2.5 percent increase in filings in the state.

My results suggest that the relationship between benefits and filings cannot be understood in isolation from the relationship between benefits and unemployment. When benefits are low, an increase in the unemployment rate leads to a decrease in the eviction filing rate. When benefits are high, an increase in the unemployment rate leads to an increase in the eviction filing rate. These relationships hold to a lesser extent during and after the Great Recession. These results are consistent with the literature on landlord-tenant interactions, particularly serial filings.

Landlord-tenant interactions are best viewed from the landlord's point of view (Garboden and Rosen, 2019). Eviction judgments are costly to landlords. "From a landlord's perspective, even the most straightforward evictions result in 2 months of lost rent plus turnover costs" (Garboden and Rosen, 2019). Although eviction judgements lead to the removal of a problem tenant, it comes with the costs associated with going to court, turning over the unit, and finding a new tenant. Qualitative research from Baltimore, MD, Cleveland, OH, and Dallas, TX suggests that landlords prefer a tenant to a vacancy (Garboden and Rosen, 2019).

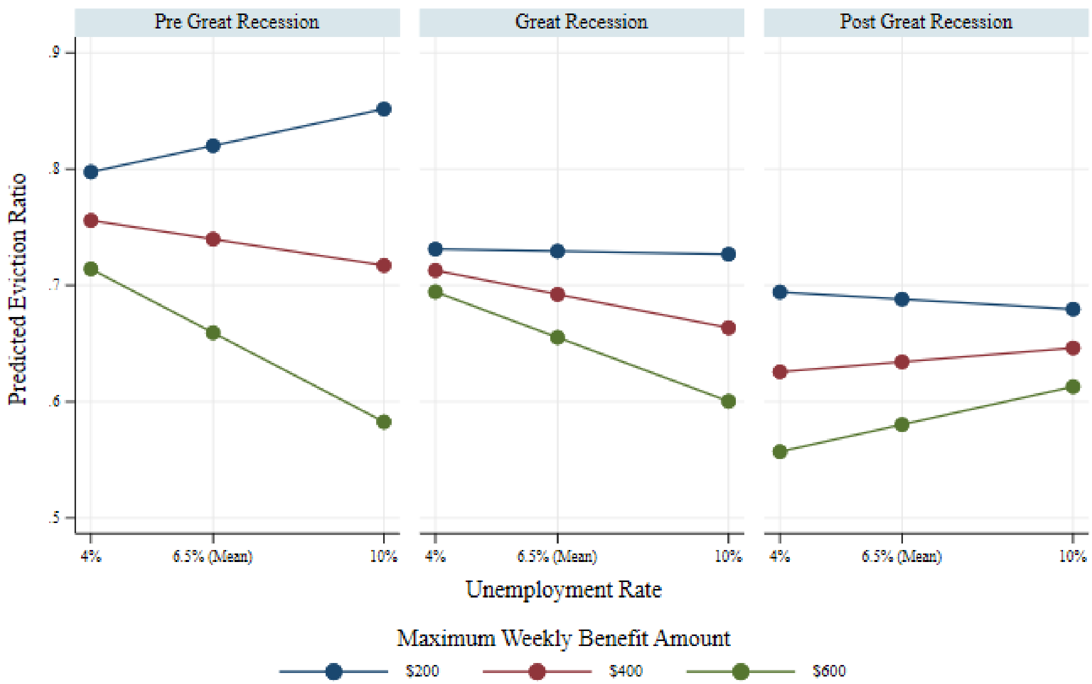
There are two actions a landlord can take when dealing with a problem tenant: filing an eviction to reach an eviction judgment (Type 1) or filing an eviction to reach an eviction filing (Type 2). Because an eviction judgment is costly, a landlord will file to reach an eviction judgment only when they believe their tenant will not pay their back rent (Garboden and Rosen, 2019). An eviction filing, on the other hand, is not costly. Eviction filings allow a landlord to reach an eviction judgment if needed. Further, eviction filings can induce a tenant to pay and can give the landlord the opportunity to collect late fees (Garboden and Rosen, 2019). These benefits lead to much of the serial eviction filings we see across the US. As a result, many landlords will file not to reach an eviction judgment, but simply for the sake of filing to receive any of these benefits.

When benefits are low, landlords may perceive that there is less of a social safety net. Therefore, as unemployment increases, landlords may be more likely to file for eviction to reach eviction judgement, because they know their tenants will not be able to pay their back rent. This logic explains the decrease in eviction filings that we see when unemployment rates increase. Essentially, landlords may be switching from Type 2 landlords to Type 1 landlords. By contrast, when benefits are high, landlords may perceive that there is more of a social safety net. As unemployment increases, landlords may be more likely to file for eviction to reach an eviction filing, because they know their tenants will eventually be able to pay as a result of their benefits. This logic explains the increase in eviction filings that we see when unemployment rates increase. Landlords are filing to file, which likely results in even more eviction filings, because individuals are remaining in their homes, but behind on their rent.

I can use additional data to support this story. If landlords are behaving more like Type 1 landlords, that is, filing to evict, we should see eviction judgments remain constant or increase compared to eviction filings. As a result, the likelihood of eviction should remain constant or increase. If landlords are behaving more like Type 2 landlords, that is, filing to file, we should see eviction judgments decrease compared to eviction filings. As a result, the likelihood of eviction should decrease.

Figure 7.5 depicts the predictive margins of the main regression model (column 3 of Table 7.6) with the likelihood of eviction as the outcome of interest. I focus on the pre–Great Recession period, as this likely captures the effect of UI benefits on eviction outcomes through the landlord's decision. In the pre–Great Recession period, when benefits are low, an increase in the unemployment is positively associated with the likelihood of eviction. When benefits are high, an increase in the unemployment rate is negatively associated with the likelihood of eviction. These results exactly match my landlord decision story. When benefits are low, landlords behave like Type 1 landlords; while when benefits are high, landlords behave like Type 2 landlords.

Figure 7.5 Predictive Margins
The Effect of UI Benefits on Likelihood of Eviction



Finally, the interaction between benefits and unemployment, and that interaction relationship with eviction filings remains during and after the Great Recession, albeit it decreases. In the context of the preceding discussion, this result suggests that during times of economic recession landlords may be less sure that their tenant will eventually be able to pay and less sure that they will be able to find a satisfactory new tenant. These negative impacts on the likelihood of filing for eviction mitigate the positive relationship between benefits and filings. This outcome persists even after the Great Recession due to the slow recovery and potentially lasting change in the interactions between landlords and tenants.

Conclusion

In this paper, I study the effect of UI benefits on rental housing evictions. To do so, I exploit differences in UI generosity across states and over time. I find that county-level eviction filing rates increase as state-level benefits become more generous. This positive relationship is smaller during and after the Great Recession. Despite what intuition may indicate, these results make sense within the framework of the landlord-tenant relationship. Landlords are more likely to file when they are sure that their late tenants will eventually pay. Although the effects are somewhat small at the county-level, the aggregated effect can be larger. For example, a $1,000 increase in maximum benefit generosity in North Carolina could lead to 3,848 additional eviction filings in the state.

These results suggest that increases in UI generosity can lead to unintended consequences for renters. However, these results do not mean that policymakers should refrain from increasing UI generosity and cannot rely on unemployment insurance as an eviction diversion program. My results suggest that we need to think more clearly about how we create and implement eviction diversion programs. Preventing eviction filings requires delivery of benefits in advance of the day rent is due. If tenants are late on their rent, they will continue to be filed on.

Additionally, these results highlight the importance of understanding the landlord-tenant relationship. When studying eviction, the literature has focused almost exclusively on the tenant's perspective. Although tenants certainly suffer a larger fallout from eviction, the landlord perspective is incredibly important. If we do not understand the landlord-tenant relationship, we will never be able to understand why certain programs, like unemployment insurance, are not preventing filings like our intuition suggested they would. Ultimately, we need a clear understanding of the mechanisms through which evictions take place if we wish to prevent evictions.

CHAPTER VIII

CONCLUSION

This dissertation studies the prevalence and prevention of rental housing evictions. It expands the literature in several ways. First, it summarizes the eviction literature to date, finding that the over the last 20 years, the eviction literature greatly increased. Additionally, the topics covered in the literature fall in one of five different categories: prevalence, causes, consequences, prevention, and landlords. Second, it develops a theoretical model of the eviction rate, which incorporates both the landlord and the tenant perspective. Although eviction involves both the landlord and the tenant (as well as the court), it is a decision made by the landlord that begins the process. It is important to have a clear understanding of when the landlord makes this decision and what the implications are for aggregate eviction outcomes.

Third, this dissertation discusses and uses the Eviction Lab data. The prior literature is limited in its conclusions due to a lack of national data. Now that there is a national database it is important to evaluate the database in terms of usability. This dissertation establishes an adjustment measure for using the state-level data in the Eviction Lab.

Finally, the paper uses the Eviction Lab data to answer three questions. First, it explores the extent of the US eviction crisis. My dissertation concludes that the eviction crisis is primarily characterized by a consistently high rate of eviction filings and eviction judgments at the national, state, and local level. Further, the crisis does not appear everywhere. Certain counties have very high levels of filings and judgements, while others do not. Second, it examines the determinants of differences in eviction rates across US counties. It finds that both demographic and economic factors are associated with differences in eviction rates. Third, this dissertation examines the potential of unemployment insurance to serve as an eviction prevention program. I find that unemployment insurance does seem to aid renters, but also seems to induce landlords to file on their tenants more often. As a result, the effectiveness of unemployment insurance as an eviction prevention program is complicated.

Overall, this dissertation contributes to the literature on eviction by providing new insights. My results ultimately help better understand eviction and provide clarity to policymakers and private organizations that hope to reduce or prevent rental housing evictions in the US.

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I include a measure of real GDP per capita, which I take from the Bureau of Economic Analysis from 2002-2016; the Housing Price Index (HPI), which I obtain from the Federal Housing Finance Agency; the state-level unemployment rate, which I collect from the Bureau of Labor Statistics, Local Area Unemployment Statistics; and state annual wages from the.

APPENDIX A.

Although the graphical analysis suggests that higher benefits lead to lower average eviction filing rates, the graphical analysis does not account for other county or state-level controls. Once some of these things are accounted for the results change. Table A1 presents these results. In column 1, I present the difference in average eviction filing rates between the high and low benefit groups from Figure 1. In columns 2 and 3, I present these same estimates controlling for state fixed effects and state fixed effects and state controls, respectively. Although column 1 shows consistently lower average eviction filings for the high benefit group, columns 2 and 3 show consistently higher average eviction filings for the high benefits group. State trends are important to control for, so it is important to control for state fixed effects. The inclusion of these effects changes the results from intuitive to counterintuitive.

Table A1. Average Eviction Filing Rates over Time by UI Benefit Groups

	Average Eviction Filing Rate		
	(1)	(2)	(3)
2003 × High Max Benefit	-0.0329	0.446^{***}	0.593^{***}
	(0.182)	(0.156)	(0.164)
2004 × High Max Benefit	-0.242	0.282^{*}	0.568^{***}
	(0.182)	(0.156)	(0.176)
2005 × High Max Benefit	-0.0895	0.423^{***}	0.813^{***}
	(0.181)	(0.155)	(0.188)
2006 × High Max Benefit	0.117	0.616^{***}	1.231^{***}
	(0.181)	(0.155)	(0.204)
2007 × High Max Benefit	-0.396^{**}	0.350^{**}	1.206^{***}
	(0.184)	(0.159)	(0.231)
2008 × High Max Benefit	-0.430^{**}	0.307^{**}	1.333^{***}
	(0.181)	(0.156)	(0.255)

2009 × High Max Benefit	-0.758***	0.161	1.189***
	(0.181)	(0.155)	(0.298)
2010 × High Max Benefit	-0.610***	0.291*	1.421***
	(0.181)	(0.156)	(0.317)
2011 × High Max Benefit	-0.509***	0.309*	1.625***
	(0.189)	(0.163)	(0.340)
2012 × High Max Benefit	-0.837***	0.184	1.692***
	(0.180)	(0.152)	(0.333)
2013 × High Max Benefit	-1.130***	0.347**	1.934***
	(0.180)	(0.153)	(0.345)
2014 × High Max Benefit	-1.117***	0.284*	2.096***
	(0.181)	(0.154)	(0.375)
2015 × High Max Benefit	-1.016***	0.286*	2.282***
	(0.183)	(0.155)	(0.401)
2016 × High Max Benefit	-0.986***	0.275*	2.361***
	(0.182)	(0.154)	(0.410)
Constant	3.055***	2.859***	-31.28***
	(0.127)	(0.105)	(7.086)
State fixed effects	No	Yes	Yes
State controls	No	No	Yes
Observations	39393	39393	39393
R^2	0.0233	0.3816	0.3823

Notes: This table presents results from a regression of eviction filing rates on the interaction between years and the benefit groups. As a result, these estimates are the difference between the average eviction filing rates for the high benefit group versus the low benefit group.