Forced Out:
Race, Market, and Neighborhood Dynamics of Evictions

Timothy A. Thomas

A dissertation
submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy

University of Washington

2017

Reading Committee:

Kyle Crowder, Chair

Stewart Tolnay

Nathalie Williams

Program Authorized to Offer Degree:
Sociology

University of Washington

Abstract

Forced Out:
Race, Market, and Neighborhood Dynamics of Evictions

Timothy A. Thomas

Chair of the Supervisory Committee:
Professor Kyle Crowder
Sociology

Research on evictions highlights the hardships that low-income families face through structural constraints of stagnant wages failing to meet monthly rent. This area of study expands our understanding of the reproduction of urban poverty and improves urban sociological scholarship by examining households that do not move by choice, but are forced out. While this field of research has focused mostly on household-level dynamics, there has not been an extensive ecological evaluation on the broader metropolitan and neighborhood-level effects that contribute to the geographic concentration of evictions. This dissertation bridges that gap by analyzing neighborhood ethno-racial compositions, socioeconomics, and housing market dynamics related to evictions in King County, WA. Results show that neighborhood racial diversity, higher poverty, affordable housing, and market demand predict higher rates of evictions. Nearby neighborhood effects, such as low-rent and low-poverty, has a large impact on local eviction rates. Furthermore, neighborhoods that saw increases in Black and Latino populations and declines in education and new movers over time also see higher rates of eviction. This study highlights how place-based racial and economic inequality is shaped by the history of the political economy of the region, segregation, and housing exclusion that produced the contemporary eviction concentrations we see today.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACKNOWLEDGMENTS

I would like to deeply thank Kyle Crowder and Stew Tolnay for their persistent support and guidance over the years; I could not have made it this far without your mentorship. Thank you Nathalie Williams for challenging me to be a better scholar and Thaisa Way for your enthusiasm and encouragement.

To Eric Dunn at the Virginia Poverty Law Center, Sandra Park and Prachi Dave at the ACLU, and Scott Crain at the Northwest Justice Project, thank you for the opportunity to work on this important topic, funding, and legal guidance. Thank you Matthew Desmond for referring me to this group, data sharing, and feedback. I appreciated the opportunity to present early versions of this work and receive valuable feedback from the West Coast Poverty Center's Housing Round-table, The Contexts Working Group, and the Sociology Deviance Seminar at the University of Washington.

To Steve Pfaff, Karen Snedker, Michael Esposito, and Mariah Vignau Lorie, thank you for your friendship, support, and discussions that helped me improve various sections. Thanks to Greg Hinckley, Mohammad al-Madani, and Stephen Matthews for inspiring me early on in my academic career. To Alison Yates, thank you for encouraging me to start this path. Thank you to my good friends Erin Dana, Jessie Kindig, Rob Anderson, Kirsten Snyder Eklund, Aubrey Jenkins, Heather Gudmundson, Alice Pederson, Tiffany Grobelski, Michael Babb, Erin Carll, Sarah Reinecke, Ryan Gabriel, and Corey Hau for supporting me through this process. A special thanks to my family for their persistent love and encouragement. Finally, thank you C.B. for all that you've done.

DEDICATION

to Earl, a man I met only once but changed my path forever

Chapter 1
INTRODUCTION

In April of 2015, Ms. Stephens, an African-American woman, visited an apartment complex in South King County, WA. With her housing voucher in hand, she viewed two units and then sat down with the property manager to begin the application process. While the manager asked routine questions about Ms. Stephens background and credit history, she disclosed that she had previously been sued for unlawful detainer[1] back in 2012. The reason: falling behind on rent. Luckily, Ms. Stephens worked out a payment plan with her landlord and successfully repaid her owed dues. However, given this new information, the property manager refused to process, or even accept, the application due to her eviction record. Humiliated and discouraged, Ms. Stephens was forced to continue her search for housing elsewhere.[2]

For over 5,000 households a year in King County, Ms. Stephens story is far too common. The mark of a contested eviction[3] follows a householder for years, preventing them from accessing decent homes in good neighborhoods, leading to excessive hardships, poor health, and increasing economic and social instability (Desmond and Kimbro, 2015). For low-income households, the threat of an eviction is ever increasing as minimum wages and welfare stipends have not increased at the rate of inflation and rent (Desmond, 2012). While urban sociologists and policy scholars have long studied the effects of housing, poverty, and residential mobility, few have investigated

---

[1] A court ordered eviction process ordered by a landlord to remove a tenant.

[2] This story is drawn from a legal case that is in pre-trial. Names are changed to protect the clients.

[3] A non-contested eviction occurs when a tenant moves out before the posted due-date of the landlords eviction notice, providing no formal record of removal. When a tenant remains past the due date of the eviction, they are unlawfully detaining the premises and the landlord then moves to formal, or contested, eviction proceedings. This distinction is further explained in Chapter 2.

the direct mechanisms that lead low-income households into eviction and its consequences. To address this, research on evictions has grown over the past few years to understand this lesser known population that moves not by choice, but are forced out.

This body of work so far has examined evictions mostly at the household-level, finding the main mechanism of rent-burden playing a vital role as low-income families struggle to meet monthly rents (Desmond, 2012). However, few studies have examined neighborhood level dynamics that might be affecting evictions from the top-down. The rental market, alone, is a spatial process responding to the economic and demographic growth of a city, where spaces become commodified due to their location, amenities, and socio-economic conditions (Logan and Molotch, 1987). Populations are channeled into better and worse neighborhoods, in part through socioeconomic achievement and in part through discrimination (Oliver and Shapiro, 2006). With population growth comes increasing demand, where low-income families face higher likelihoods of eviction if their neighborhood becomes a preferred destination due to its affordability (Atkinson, 2002; Smith, 1996). This, in turn, can threaten displacement and compounding hardship on already disadvantaged families (Maly, 2005). However, even simpler dynamics than neighborhood change can threaten eviction. Most low-income households live in the poorest neighborhoods where even the slightest annual increase in rent tends to outpace their stagnant wages (Desmond, 2012).

The goal of this dissertation is to examine these neighborhood level processes of change, housing markets, and race to see how they relate to the geographic concentrations of evictions. As indicated in the vast body of research on residential mobility, segregation, and stratification, place matters when it comes to social processes (Krysan et al., 2015; Sampson, 2012). I believe that this also holds true for the progression of evictions. At the neighborhood-level, social processes help shape family opportunities through networks, economics, health, education, and safety. In high-poverty neighborhoods, these conditions can lead to worse circumstances, where racial and economic segregation can lead to concentrated poverty and social problems. All these factors contribute to household level conditions that impact housing stability for low-income families.

1.1 Who Gets Evicted?

In King County, WA alone, about 20 households are sued for contested eviction every day that court is in session.[4] Research in Milwaukee shows that the majority of the evicted are Black, female, and poor (Desmond, 2012). At the heart of the problem is rent-burden (tenants contributing more than 30% of their income to rent), which can double the chances of eviction (Wyly and Hammel, 2004; Zuk et al., 2015). Evicted low-income households contribute upwards of 90% of their income to rent, where fixed incomes are threatened by any unexpected expenses, resulting in economic instability, hardships, and even loss of children given the negative circumstances (Desmond et al., 2013; Desmond and Kimbro, 2015). The likelihood of eviction increases with the number of children present in the home, job loss, and the number of negative social ties (individuals who experienced poverty shocks such as evictions, incarceration, teen pregnancy, etc.) (Desmond and Gershenson, 2017).

At the neighborhood level, the highest rates of eviction occur in the poorest and most disadvantaged neighborhoods, with most removals occurring in Black and diverse neighborhoods. Even in White neighborhoods, Black and Latino tenants are evicted 2.5 and 1.8 times more than White men and women (Desmond, 2012). This coincides with the long history of evictions as a result of racial competition for housing, fueled by racial discrimination (Connolly, 2014). As instigators of eviction, landlords play a vital role as they respond to both household conditions of their tenants (e.g., falling behind on rent and breaking rules) and economic forecasts that motivate them to optimize profits when demand is high (Desmond and Gershenson, 2016). Landlords can also take the role of judge when they evict problem residents to send a message to surrounding tenants in the case

[4]Contested evictions are legal cases filed by landlords to evict tenants who are "unlawfully detaining" a rented home after the date they were supposed to leave. A non-contested eviction occurs when a tenant moves on, or before, the due date. There is no data available on non-contested evictions at this time.

of criminal activity (Hamilton-Smith, 2002). However, these stricter enforcements often coincide with the entrance of gentrification (Byrne, 2003) where the opportunity to replace poor tenants with higher paying ones becomes a feasible option (Desmond and Gershenson, 2017). In each of these circumstances, lower-level household contexts can be closely tied to larger neighborhood dynamics of population growth, rent, economics, race, and social organization.

1.2 The Case for Neighborhood Research and Evictions

Historically, neighborhood dynamics are central to household outcomes. Early contributions from the Chicago School developed an ecological definition of the city as an ever-changing organism where parts of the city take over others in a battle for primacy and resources (Burgess, 1925). Later work on segregation found important associations between racial isolation, extreme poverty, and economic decline due to job loss and divestment (Massey and Denton, 1993; Wilson, 2012). These areas suffered social disorganization that affected family structures, health, social and economic wellbeing, and generational outcomes (Sampson et al., 2002; Sharkey, 2008). More contemporary analyses have linked residential segregation and over-representation of Black and Latino households in the foreclosure crisis and generational transmission of poverty for minority households (Hall et al., 2015; Rugh and Massey, 2010; Sharkey, 2008).

Neighborhoods represent the broader political economy of a city where agents and actors attempt to optimize the market, allowing some households to benefit while others become more disadvantaged (Logan and Molotch, 1987). By its nature, the neighborhood is the main ingredient for household opportunity through the process of social organization and safety, education opportunities, and economic prosperity through owning a home and other factors that positively relate to economic improvement. However, history provides a dark tale about the racially disparate effects of where households reside.

Over the 20th century, legalized and informal discriminatory practices in housing opportunity, such as those demonstrated through the FHA loan process and private lending, have prevented minority households from participating in the growth of the middle class. These practices and consequences are tied to location where lenders denied credit for households living in minority neighborhoods while, at the same time, homeowners in these locations saw much lower appreciation in value than their White counterparts in White segregated neighborhoods (Oliver and Shapiro, 2006). This resulted in both the economic decline of Black communities and excessively high rates of renting among Black households; leaving little equity for the next generation while simultaneously providing substandard education and training for better prospects (Aratani et al., 2011). By the 1980s, gentrification became a common household terminology as large numbers of urban spaces started to see reinvestment and revitalization (Lees et al., 2007). However, financial investments were divided by race, denying loans to Black households based on location and bad credit (Wyly and Hammel, 2004). Neighborhoods saw further decline as Black middle-class households exited the city for the suburbs, leaving behind poor households facing greater economic disadvantages (Wilson, 2012).

By the turn of the 21st century, the service and tech industries increased the attraction of the inner-city, where population growth increased demand for affordable spaces, leading to the succession of nearby disadvantaged neighborhoods. With increased demand in these formerly segregated spaces, low-income tenants faced rent hikes and stricter rules from landlords, which led to displacement through pricing out and formal eviction, often to even more disadvantaged neighborhoods (Amato and Manuel, 2012; Formoso et al., 2010; Maly, 2005).

Households are primarily evicted due to internal poverty and external pressures of housing costs.. Yet, evidence from the history of discriminatory housing practices suggests that location of the household has a dynamic effect on evictions, which is tied to social organization, networks, rent, demand, demographic composition, education, economics, and various form of neighborhood change for the better or worse. So far, what we know about location and evictions is that low-income households face high risks of removal when they live in steadily disadvantaged or changing neighborhoodsnot so much in more socioeconomically advantaged and wealthier ones. In other words, persistent household poverty through eviction is closely tied to the type of neighborhood in which the family lives.

Focusing on the ecology of contested evictions, this research aims to address the following research questions: What racial groups face the highest risk of evictions and where? To what extent do local and extra-local neighborhood conditions (e.g., neighborhood-level SES, rent, and racial composition) influence eviction rates? And, what neighborhood change characteristics are most pronounced in the concentration of evictions?

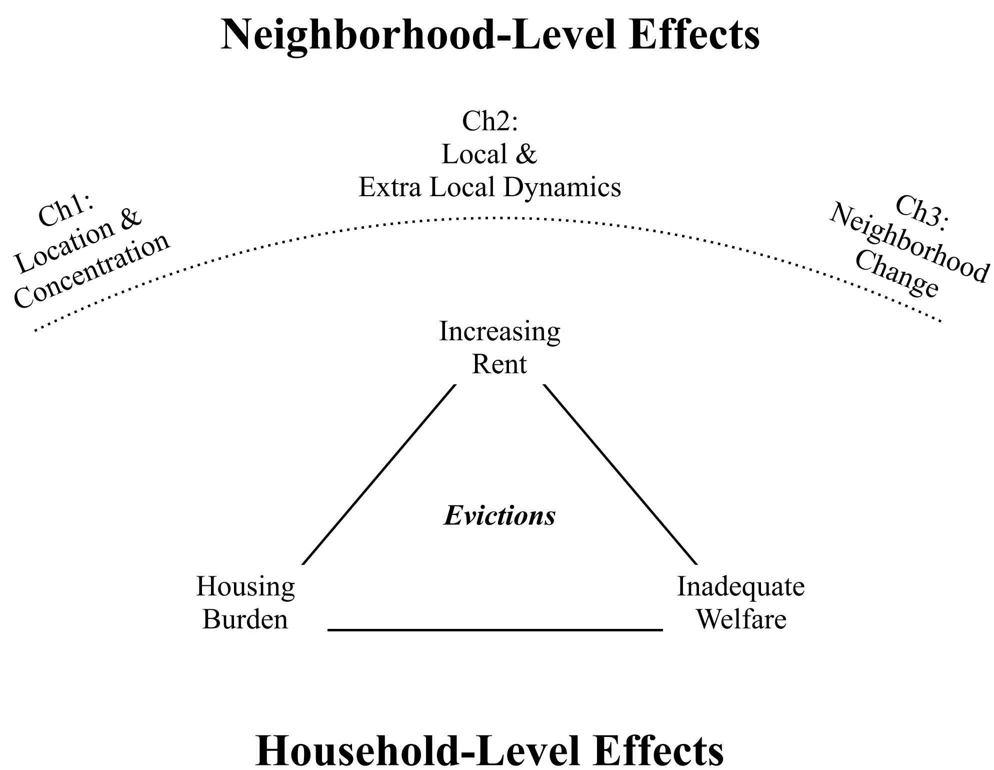
1.3 Outline of the Dissertation

I argue that neighborhood location not only is related to evictions, but helps predict its likelihood (Gault and Silver, 2008) given the factors of neighborhood racial composition, socioeconomics, and the rental market. I demonstrate this through an in-depth analysis of these three characteristics at the neighborhood level. Formatted as three standalone articles, this dissertation examines these neighborhood relationships using unlawful detainer court records in King County, WA, combined with US Census and Zillow rental data.

In this research, I take an ecological approach to evictions, which posits that the household level mechanisms of poverty interacts differently within contrasting neighborhood dynamics. The diagram in Figure 1.1 helps demonstrate this dynamic and outlines the research focus of the three chapters. At the bottom are the three household-level structural constraints associated with evictions, where household economic burden and inadequate welfare fail to compete with rent. The likelihood of eviction increases when low-income household conditions include job loss, the number of children present, or a criminal or eviction record. At the top of the diagram is the overarching neighborhood dynamics associated with evictions (the focus of this research), where concentrations vary by local, nearby, and temporally shifting neighborhood dynamics. For example, housing demand increases with population growth and desirability of a neighborhood, where preferred areas may see higher rent while more disadvantaged ones see lower rents. Furthermore, the local economy, historical development of the neighborhood, segregation, and residential mobility sort different socio-demographic groups in various neighborhoods. These conditions should demonstrate some distinct spatial pattern of high and low concentrations relating to the neighborhood dynamics in which households live.

The first chapter establishes the foundation through a descriptive exploratory spatial data analysis of the location and concentration of evictions in relation to neighborhood rent-burden, race, and rent. I also explore broad racial differences in evictions among White, Black, Latino, and Asian households using a unique demographic estimation technique. The second chapter builds on the first by modeling the local and extra-local neighborhood effects on evictions. This section is the first attempt at defining a spatial theoretical framework for predicting evictions based on the neighborhood housing market, racial stratification, and nearby effects on the local eviction rate. The extra-local effects also help reveal possible connections to sociodemographic competition for space based on nearby market conditions. Finally, the third chapter explores changes in neighborhood rent, socioeconomic status, and racial composition. This analysis uncovers the different types of shifts that may commonly precede evictions while testing the effect of population growth and demand on eviction rates.

Figure 1.1: Ecological Evaluation of Evictions Diagram



Chapter 2

NEIGHBORHOOD & DEMOGRAPHIC DISPARITIES IN EVICTIONS

2.1 Introduction

On all fronts, evictions worsen life chances. The mark of an eviction can follow a person their entire life; preventing them from securing decent and affordable housing; resulting in unintentional mobility to disadvantaged neighborhoods with higher poverty and crime; forcing them to move into worse housing conditions; loss of personal property; declining health; and even homelessness (Casciano and Massey, 2012; Crane and Warnes, 2000; Desmond, 2012, 2014; Desmond and Kimbro, 2015; Dwyer and Phillips Lassus, 2015; Shaw, 2004; Strahilevitz, 2008). However, little is known about the racial differences among the evicted or to what extent neighborhood characteristics may be associated with, or even driving, them. Given that minority households rent at a higher rate than Whites (31% White, 42% Asian, 58% Black, 54% Latino, and 59% other), they are de facto at a higher risk of evictions than Whites. Furthermore, urban sociology research demonstrates significant connections between where low-income and minority populations live and persistent disadvantage (Charles, 2003; Massey and Denton, 1993; Sampson et al., 2002).

The few studies that have directly examined evictions provide important household, and sometimes neighborhood-level, dynamics related to this life event. Studies within Milwaukee find that rising housing costs, stagnant wages, loss of work, and an inadequate welfare system are key structural household constraints leading to evictions with most of these events occurring in poor and minority neighborhoods (Desmond, 2012). While revealing, these findings suffer from limited generalizability (i.e., national representativeness). For example, Milwaukee has a large, segregated Black population and relatively high poverty. How might disparities in evictions manifest in other regions with more racially integrated or wealthier neighborhoods?

Prior research on neighborhood segregation and residential mobility provide some guidance on what neighborhood relationships may be more salient for evictions. The most tangible example involves housing market shifts and gentrification where increasing competition for land raises local housing prices while demolishing older, affordable homes (Formoso et al., 2010). Segregation literature discusses how hypersegregation produces concentrated poverty, reductions in wealth accrual, and exposure to negative social and physical conditions (Massey and Denton, 1993). Furthermore, the residential segregation literature reflects on historical consequences of discrimination and persistent inaccessibility of better neighborhoods for different racial groups (Charles, 2003). These studies all point to social stratification that is place dependent and persists along racial lines.

The goal of this study is to conduct an ecological evaluation of evictions by examining the racial, spatial, and sex differences in evictions through a descriptive investigation of household-level demographics and neighborhood-level compositions associated with the geographic concentration of evictions. To accomplish this, I employ demographic estimation techniques to find the race and sex of all eviction defendants within the data, providing a broader examination of household-level racial disparities that previously relied on individual-level survey data for demographics. Next, I utilize a neighborhood effects framework on evictions to understand possible spatial associations and drivers of evictions using data from King County, WA. This study expands prior research by examining how evictions play out in a racially and economically different metropolitan area as compared to Milwaukee, WI, providing a unique opportunity to see how a metro with integrated neighborhoods and rapidly rising housing costs might relate to these events. I begin with a theoretical review of evictions and neighborhood effects research. I then examine descriptive results of race and sex differences of evicted households followed by a neighborhood level descriptive analysis of racial, economic, and housing market variables in relation to evictions and end with a discussion of the findings. These results provide a foundational understanding that will inform more complex models in the following chapters.

2.2 Theory & Background

2.2.1 Household Dynamics of Evictions

The most extensive analysis of evictions thus far comes from data in Milwaukee, Wisconsin where 3.5% of all renters were evicted. Women took the highest share (60.6%) while supplemental court surveys showed Black households were overrepresented in eviction cases (71% Black, 21% White, 5% Latino, and 3% other) (Desmond, 2012). Over 69% of those surveyed were women, most of whom were Black mothers living with children. Many evicted tenants did not know where they were going; some to a friends home, an unknown location, or entering homelessness. Ages of the evicted ranged between 19 and 69, with 94% of defendants receiving no housing assistance. Their median monthly income was $935 while paying, on average, $540 a month in rent (over 57% of their income) and owing on average $900 in delinquent rent (Desmond, 2012). Studies find that mothers with evictions face greater material hardship than any other group, with a higher likelihood of suffering mental and physical health problems, and facing worse outcomes for their children even years after dealing with an eviction (Desmond and Kimbro, 2015). Competitive housing markets, stagnant wages, and an inefficient welfare system are primary mechanisms that lead to eviction (Desmond, 2012). One of the main challenges for low-income tenants is rent-burden (over 30% of household wages spent on housing) where families are forced to devote larger portions of their income to housing while minimizing the amount they can spend toward other necessities such as food, education, medication, and transportation (Desmond and Kimbro, 2015; McConnell, 2012; Newman and Holupka, 2014). Studies show that at least 80% to 90% of households were evicted for falling behind on rent with about 1/3rd of households allocating at least 80% of their income to rent (Brophy and Smith, 1997; Desmond, 2015). Unexpected expenses with low fixed incomes can lead to involuntary displacement or even removal of children if they are found to be living in unhealthful environments (Desmond, 2012; Desmond and Kimbro, 2015). In a survey of renters, tenants race did not predict an eviction, however, evictions were positively related to the number of children present in the household, prior evictions, recent job loss, and higher crime in the neighborhood, net of other effects (Desmond and Gershenson, 2017). Sadly, this scenario is not uncommon. Over recent decades, housing insecurity has increased by over 30% and is projected to grow even more by 2025 (Dwyer and Phillips Lassus, 2015).

2.2.2 Neighborhood Correlates and Drivers of Evictions

The mark of an eviction can limit access to quality housing in preferable neighborhoods (Casciano and Massey, 2012). Even if an evicted household can achieve housing, they tend to be displaced to neighborhoods with higher disadvantage, crime, and environmental hazards. Stagnant wages and increasing housing costs make it harder to maintain housing, especially for women who have smaller incomes with much larger expenses with the presence of children (Desmond, 2015; Desmond et al., 2013).

While these findings help explain household level mechanisms of evictions, less is known about neighborhood characteristics that may be associated with, or even driving, eviction rates. Research from Milwaukee, in conjunction with extant neighborhood effects research, provide several theories on ecological correlates and drivers of evictions. By correlates, I refer to different racial and economic compositions of the neighborhoods that may be related to the geographic distribution of evictions. By neighborhood drivers, I refer to the impacts of the housing market and social control enacted by agents who optimize market shifts by clearing space for higher paying tenants.

Neighborhood Race & Poverty Correlates

The minority composition of a neighborhood may be one possible correlate to evictions. Current research on evictions finds that the highest rates of eviction occur in Black, mixed-race, and disadvantaged neighborhoods (Desmond, 2012; Desmond and Gershenson, 2017). Since renters are the population at risk of an eviction, the disproportionately high rate of renting among minority households suggests that these groups may be most at risk of being evicted. The reason for this disparity in renting is tied to historical exclusion from homeownership through discriminatory political and economic forces and the subsequent residential segregation in neighborhoods that physically and economically declined over time (Conley, 1999). Since the 1930s, the federal government financed and encouraged suburban growth through FHA loans that bolstered the struggling construction industry while encouraging economic growth outside of central cities (Oliver and Shapiro, 2006). To guarantee the success of their investment, government agents included race as part of the criteria in determining whether a neighborhood was worthy of receiving financial support. Mixed race, all-Black, older, and deteriorating neighborhoods were deemed undesirable while suburban areas were preferred, making urban and Black neighborhoods less likely to receive loan assistance. White households were then encouraged to purchase a home away from non-White neighborhoods, segregating themselves from Black and other minority groups (Shapiro, 2004). To further protect neighborhoods from losing home value and perceived social decline, housing covenants were established to prevent minority families from buying or moving into White communities, drawing legal lines that further segregated minority and White neighborhoods (Charles, 2003).

Even after the Supreme Court outlawed discriminating practices at the federal level, banks and realtors continued these practices through redlining (bank defined boundaries for financially risky areas that surrounded minority neighborhoods), block-busting (realtors convincing owners to sell low due to perceived threats of people of another race or class moving in while profiting from selling high to new residents), and unfairly high interest rate loans. Lack of access to good credit prevented Black households from revitalizing or buying homes in their own neighborhoods and obstructed their opportunities to exit. The lack of external investment in Black communities and the inability to exit disadvantaged urban areas forced African Americans to face concentrating social problems such as poverty, poor health, and crime. Deficient school districts reinforced generational disenfranchisement where poor education reduced childrens prospects of competing in a changing economy (Oliver and Shapiro, 2006). As these historical contexts shaped modern neighborhood conditions within respective metropolitan areas, this increasing exposure to disadvantage and declining neighborhoods prevented many Black families from participating in the wealth accrual machine of homeownership that Whites were able to achieve for decades. With little hope of ownership, renting became the more viable solution among minority populations.

During these historical events that segregated neighborhoods, employment declined and discrimination among minority, particularly Black, workers compounded disadvantage. Deindustrialization led to concentrated poverty and the out-migration of middle-class Blacks (Wilson, 2012). The resulting high geographic concentrations of poverty in hyper-segregated areas led to economic disparity, social isolation, increasing structural disadvantage, erosion of community social organization, systemic avoidance by both Whites and investors, declining political clout, and increasing costs for local governmental support (Kneebone et al., 2011; Massey and Denton, 1993; Peterson and Krivo, 2010; Sharkey, 2008). These historical contexts that deepened disadvantages for racial/ethnic minorities may be more directly responsible for higher levels of evictions in non-white segregated spaces.

By the 21st century, segregation seemed to be on the decline (Glaeser and Vigdor, 2012). Even more promising is that Black and White renters were less segregated than homeowners by the year 2000 (Friedman et al., 2013). However, while the latter half of the 20th century experienced a shift from macro-level to micro-level segregation, economic stratification increased and residential segregation between Blacks and Whites remains relatively high to this day (Krysan et al., 2015; Massey et al., 2009) meaning minorities and Whites have not achieved economic parity. One explanation is that the persistent historical exclusion from economic growth prevented Black families from developing wealth and savings that could be passed on to their children to move into better neighborhoods, buy homes, or improve their education. Research suggests that over 70% of Black children who grew up in the poorest quarter of American neighborhoods remain in the poorest quarter as adults (Sharkey, 2008).

From prior research on Milwaukee we know that evictions largely occurred in minority segregated (46%), mixed-race (30%), and disadvantaged neighborhoods (Desmond, 2012), however this trend may be metro-specific as Milwaukee has an exceptionally high level of Black-White segregation above and beyond other metros in the US (Lichter et al., 2015). Milwaukees racial composition is 36% White, 39% Black, 18% Latino, 4% Asian, and 3% other (US Census Bureau, 2017). In White neighborhoods, women and men were evicted evenly, however, women in Black and Latino neighborhoods face higher odds of evictions (2.5:1 and 1.78:1, respectively). Work by Greenberg, Rohe, and Williams 1982 found that Latino tenants in predominantly White neighborhoods were twice as likely to be evicted than other neighborhoods and more likely to be evicted when the landlord was non-Latino. Examining neighborhood eviction patterns in a lower minority metro with more integrated neighborhoods would greatly improve our understanding of the ecology of evictions.

Housing Market Drivers Neighborhood drivers of evictions revolve around housing market forces that respond to increased demand and competition for spaces, especially in economically thriving cities. This relationship between market forces and evictions is closely tied to dynamics of neighborhood change where the political economy of the city optimizes capital through the commodification of spaces and maximizing profits in response to increasing demands (Logan and Molotch, 1987). Most neighborhoods see a steady increase in rent due to inflation and rising housing costs such as increasing taxes and upkeep. The most desirable neighborhoods tend to be more expensive and affordable to higher-earning households while low-income households are relegated to the least expensive and, usually, most disadvantaged neighborhoods. Even in high-poverty neighborhoods annual rents increase where stagnant household incomes and welfare stipends are unable to compete leading to removal when falling behind on rent (Desmond, 2012).

Rapid changes in a neighborhood can increase pressure and insecurity for a low-income household. When a disadvantaged area becomes a desirable destination, such as the common case for gentrification, political actors team with developers to introduce policy-backed strategies meant to improve areas leading to disparate socio-economic conditions between new and legacy residents (Wyly and Hammel, 2004). These shifts exacerbate low-income housing burden as large increases in the population drives up housing demand and costs while displacing low-income households through evictions or removal of affordable housing as a means to make room for higher paying tenants (Aratani et al., 2011; Desmond, 2012; Formoso et al., 2010; Maly, 2005). Therefore, living in, or even near, transitioning neighborhoods could greatly increase the likelihood of eviction.

The involuntary mobility and displacement produced by an eviction (Atkinson, 2002; Smith, 1996) leads to a lengthy process in finding housing, be it within market-rate areas or through subsidized housing. This leaves ample opportunity to endure a period of homelessness or other problems on the way to achieving housing (Curtis et al., 2013). Of the options available, suburbs are probably the most affordable. However, suburban neighborhoods tend to have weaker social services, fewer public transportation options, and potentially fewer support services and networks nearby to provide assistance in times of need (Dwyer and Phillips Lassus, 2015).

Social Control Drivers

Social control drivers largely refer to the landlords evicting tenants as a response to a mixture of local pressures and personal biases combined with broader neighborhood-level shifting dynamics such as the arrival of gentrification in an area. One major goal for policy and market driven initiatives to improve areas is to remove blight and problem tenants (Amato and Manuel, 2012). However, the choice structure on what, or who, to remove may be clouded with racialized biases that target non-White tenants over others. There is a long history of evictions due to racial competition for housing and resources, which is fueled by legacies of racial discrimination (Connolly, 2014).

Evictions can play a role in social control as an anti-crime measure, or a way to send a message to surrounding tenants that certain behaviors and activities are not accepted. These types of evictions may involve problem tenants (Braga and Bond, 2008; Hamilton-Smith, 2002) such as those participating in drug dealing or sex work (Buron et al., 2002). However, studies find a temporal association with some removals coinciding with gentrification in the area (Byrne, 2003). This raises questions about landlord motivation to evict where punitive actions may be largely related to economic optimization. More specifically, a landlord may choose to avoid evicting a tenant if the probability of replacing them with a higher earning one is unlikely (Desmond and Gershenson, 2017). In addition, the landlord would lose at least a months worth of rent (about the time it takes to remove and replace a tenant) and all possibility of recouping back-rent from a tenant who has fallen behind in payments (Garboden and Rosen, 2017). Therefore, they may choose to put up with negligent or deviant behavior if the time and cost of removing a tenant outweighs the benefit.

The introduction of new residents also disrupts the social order of neighborhoods and may increase unwanted surveillance for low-income tenants (Barton and Gruner, 2016). Gentrification tends to experience a short upswing in crime (Kreager et al., 2011) resulting in increasing surveillance in already pressured neighborhoods by both formal and informal actors (Guest et al., 2008). Furthermore, new residents may bring with them competing views on how social control should operate in their new neighborhood. This may increase the likelihood of calls to the police for any social or physical disorder, which in turn could trigger a landlord to remove a tenant who is deemed problematic or simply to avoid the trouble of dealing with the police.

2.3 Hypotheses

A heuristic that can be drawn from these theories consists of micro-level (household-level) and macro-level (neighborhood-level) connections related to eviction concentrations in specific areas. At the micro-level, evictions are directly related to economic burden (poverty) failing to meet housing costs (rent). At the macro-level, neighborhood rent is related to demand and desirability, which are functions of growth, socioeconomic composition of the population, and the broader political economy of a metro. As economic and population growth increases, political actors work with developers to improve spaces and optimize the housing market. From there, spaces become commodified and accessible to some, while inaccessible to others, where rent increase becomes a proxy for demand and desirability and may drive evictions higher. Regarding household poverty, research finds that low-income households are not only concentrated in high poverty neighborhoods, but are also largely found in minority segregated communities that have faced long periods of disadvantage, divestment, inadequate education, and lack of jobsall factors that would impact housing stability. The construction of minority segregation is related to historical exclusion and non-White avoidance in the housing market, leading to lower rents, higher poverty, and potentially higher rates of eviction in minority segregated areas that are deemed less desirable.

Given this model, I draw the following hypotheses. At the micro-level, (H1) non-White households, especially Black, should see higher rates of eviction than Whites overall and in most, if not all, neighborhood characteristic scenarios (neighborhood segregation, rent burden, and housing market). This is, in part, motivated by what we know about the history of economic disadvantage among Black households and, in part, the higher representation of Black households within the eviction literature. At the macro-level, (H2) neighborhoods with higher diversity, Black, or Latino presence should see higher rates of eviction due to these areas having experienced longer periods of disadvantage. Also, (H3) neighborhoods with higher rent-burden should see higher rates of eviction given the housing instability produced through economic burden. Lastly, if the commodification thesis posits that rent costs are related to desirability of a neighborhood, then (H4) neighborhoods with lower rent should see higher rates of eviction as these are less desirable spaces and considerably more affordable populations that may be at a higher risk of eviction.

2.4 Data

2.4.1 Eviction Records

Evictions data used in this study are all defendants from unlawful detainer cases (UDs)civil lawsuits filed by landlords against tenantsin 2013 for King County, WA.[1] In 2013, there were a total of 5,225 cases (operationalized as households from here on) and 7,242 defendants within these cases. After omitting businesses, non-geocodable addresses, and locations outside of King County, the final dataset holds 5,111 households and 7,065 individuals.

The Unlawful Detainer Process

When a landlord evicts a tenant, there are two potential outcomes. The first is a non-contested eviction where the household moves on, or before, the due date that they are required to vacate the premises. The second is a contested eviction where the household remains past the eviction date and are then unlawfully detaining the premises, requiring legal action on behalf of the landlord. This research utilizes data on the latter of these two definitions.

In the case of a household staying beyond their due date, the unlawful detainer (UD) filing is the preferred form of landlord-tenant eviction in Washington State due to their relative speed to

[1] UD case numbers and names were collected by The Washington State Low Income Housing Alliance through a public disclosure request to the Washington State Courts for data from 2004 to 2013. The Northwest Justice Project then subset the King County cases for 2013 and sent an intern to the King County Courthouse to retrieve all home addresses for each case where the defendants lived at the time of eviction. The original data received by the Washington State Courts through the request held addresses, however, further investigation showed these addresses were actually the offices of either the prosecutor or landlord. Thus, physical examination of the court documents were required to obtain the defendants unlawful detainer address. The cost of address collection from the King County Courthouse prohibited expanding the collection beyond 2013. Address locations of where the defendants lived at time of litigation were then geocoded by Matt Desmond and his team at Harvard University.

decision. UDs are typically heard, and decided, within one week of filing, and if necessary, given a trial within 30 days. In turn, this usually gives tenants little time to seek legal representation, prepare their defense, or opportunity for pre-trial discovery (Eric Dunn, personal communication, August 1, 2017). The process of an unlawful detainer in Washington State begins out-of-court with an eviction notice given by the landlord with a deadline for the tenant to leave the premises. If the tenant stays beyond the deadline, they are now unlawfully detaining the premises and are then contesting the eviction and subject to further action. From there, the landlord begins the UD filing by serving a summons and complaint on the tenant, providing reason for eviction and reparations sought through the court. If the tenant fails to respond to the summons and complaint, the court enters into a default judgment against the tenant, ordering the tenant to leave while authorizing the court clerk to issue a writ of restitutiona directive to the sheriff to physically remove the tenant from the property. At the time of filing, the tenant must respond to a show cause as to why the writ of restitution should not be ordered and then schedule a hearing within seven to thirty days. The decisive summary hearing usually lasts only a few minutes. Based on the evidence on either side, the case can be awarded to the landlord, tenant (dismissing charges), or, in rare cases, be determined to move to trial due to unclear factual records. If the landlord wins the case, and the tenant still does not leave, the landlord can apply for a writ of restitution to be issued. For the most part, few cases end in writ enforcement.[2] Causes for UD filings usually range from tenant non-payment to breaking community rules. While it is unclear what the proportion of King County UDs are due to delinquent payment or rule breaking, research suggests that around 80% to 90% of eviction cases result from non-payment (Brophy and Smith, 1997). Even though not all unlawful detainer cases end favoring the landlord, or enforcing a writ of restitution, the mark of an unlawful

[2]While writ of restitution counts would be a clear measure of physical removal through eviction, the data on writs are unfortunately unreliable. Within King County, 200 writs were enforced between 2004 to 2013. However, in Snohomish County, just north of King County, there were 17,892 writs of restitution. Reasons for this disparity are unknown, but possibly due to under-reporting or some other unknown reason. Regardless, this disparity in counts between nearby counties deems recorded writs to be unreliable in King County.

detainer remains on a householders record and can severely impact opportunities to obtain housing in future. Many landlords tend to deny new applicants based on whether they were charged with an eviction, regardless of the outcome (Casciano and Massey, 2012).

2.4.2 Unlawful Detainer Demographic Estimation

To understand demographic variation and disparities in householders and individuals (Hypothesis 1), sex and race must be estimated due to the dearth of demographic information available in unlawful detainer cases. From the cases collected, the only relevant information available are the names and locations of the tenants residence of eviction. Using these two pieces of information, sex and racial characteristics are inferred through two estimation techniques.

Sex Estimation

First, sex is inferred by cross-validating the first name of the individual with the Social Security Administration Name Registry from 1932 to 2012 and the US Census IPUMS (Blevins and Mullen, 2015).[3] Of the 7,065 defendant names, 6,446 were identified as male or female. The remaining unidentified cases had unique names that were not identifiable through the SSA registry. To assign sex to these individuals, I designed a sex recognition strategy using Facebook to manually cross-check users sex identity using profile information and images. The first name of each unidentified individual was entered into Facebooks search engine and cross-checked with the first ten results. Then, the average sex among the ten profiles was assigned to the unidentified individual. Using this method, 479 sex identities were added to the database, resulting in a total of 6,925 persons with successfully assigned sexes.

---

[3]The R package *gender* developed by Blevins and Mullen (2015) was used to estimate sex. This process is a similar technique used by Matthew Desmond (2012).

Race Estimation

Race is estimated through a Bayesian prediction model using surname and geolocation. This method developed by Imai and Khanna 2016[4] utilizes the Bayes rule to examine the racial composition of frequently occurring surnames within Census name data and the racial composition for each neighborhood (tract data) where the unlawful detainee lived to compute the predicted probability of each racial category (White, Black, Latino, Asian, or other) for any given individual. For example, a person with the last name Jackson, a common Black surname, living in a high-Black neighborhood would have a higher likelihood of being Black. Whereas the same name found in a high-White neighborhood would have a lower probability of being Black. Neighborhood racial composition is defined by the 2010 Decennial Census tract. Using this method, all 7,065 individuals were assigned a probabilistic race.[5]

Head of Household Estimation

To calculate rates of unlawful detainer cases as compared to the population of renters in King County (the population vulnerable to unlawful detainment cases), the head of household is the preferred unit of analysis over individuals. Household type is defined by the race and sex characteristics of the first defendant named in each UD case (e.g., Black female-headed household). Unfortunately, the order in which the head of household is named is not officially defined and somewhat arbitrary. However, lawyers who specialize in UD cases in King County suggest that the first person named in a case is most likely the head of household. To test this assumption, the race and sex distribution of all UDs versus single-named and multi-named defendant UD cases in

[4]The R package *wru*, Who Are You?, developed by Imai and Khanna (2016) was used to estimate race. The authors of this method test several other prediction methods and find that their Bayesian model to outperforms all other methods.

[5]Each individual is given a probability for each racial category. From these categories, the highest probability among the five categories is assigned to the respective individual. The authors of this method (Imai and Khanna, 2016) also suggest the highest probability as the strongest choice as it reduces misclassification.

the data were compared to each other. The number of defendants named in a UD case range from one (67% of cases), two (28% of cases), or more (5% of cases) persons. Each additional defendant could be a spouse, family member, a roommate, or some other household member.[6] Overall, the differences in rates of eviction for all, single, and multi-named defendants are relatively similar (i.e., within one to two percentage points, see Table 2.1 for more detail). Since the proportions are similar for multi-named and single-named cases, this provides good evidence that the first person named in a case is the head.[7] In the end, race is estimated for all 5,111 householders[8] and sex is estimated for 5,017 householders.

Race and Sex Combination Among Renters in King County Estimation

With the race and sex of unlawful detainment householders in hand, the rate of unlawful detainees for various groups can be calculated by dividing the count of unlawful detainment householders of a given group by the total number of renters for the respective group within the 2010 Decennial Census. Eviction rates by sex and by race, exclusively, is uncomplicated. However, examining the rate of householder unlawful detainment for the combined race and sex of householders is a little more complicated due to missing data within the census. The purpose of withholding data within the census is to improve anonymity among survey participants. This means that the Census Bureau withholds certain table combinations. For example, they provide the race of head of householders

[6]Due to Washington State laws, minors are typically not named in unlawful detainer cases. This means that families with or without children are not easily identifiable. In addition, there is no clear protocol in naming the number residents in an unlawful detainer case. Persons named in a case are at least the leaseholder, and may include other adults cited by the landlord in the case (e.g., partner, roommate(s), spouse). This makes the data a conservative estimate of how many tenants face evictions.

[7]A second check on head of household order was conducted through a phone interview with the lead lawyer from King Countys Housing Justice Project (HJP) (see Table 2.9 for additional details). While not always the case, the HJP also suggests that it is safe to assume that the first person named in a case is the head of household. In addition to this insight, the defendant rates by sex and race representation among their clients are similar to those found in this study. The Housing Justice Project collects sex and race statistics from their roughly 1,500 unrepresented clients a year, a subsample of the full population of those facing unlawful detainment cases (Rory O'Sullivan, personal communication, November 28, 2016). This finding provides additional confidence in the race and sex estimations described earlier.

[8]Householder is synonymous with head of household.

in one table and the sex of head of householders in another. The combination of the two is not provided, the elements of a table that is necessary to determine rates and rate ratios of householders by combined sex and race. To remedy this, I calculate the expected values of the combined race and sex of all householders within each tract using the total counts of householders by race (n_{+j}), total counts of householders by sex (n_{i+}), and the grand total (n_{++}). [9]

$$\frac{n_{i+} \cdot n_{+j}}{n_{++}}$$

This estimation provides the necessary information for the denominator of the eviction rate for the given racial and sex combinations (e.g., Black-female headed householders).

2.4.3 Neighorhood Contexts

To understand possible neighborhood dynamics associated with the spatial distribution of evictions (H2 through H4), I include racial composition, economic, and housing market characteristics within tracts of King County. Neighborhood contexts are drawn from the 2010-2014 ACS 5-year estimates normalized to the 2010 US Census Decennial tract boundaries within King County, WA. Arguably, tracts are not a perfect definition for neighborhoods as residents tend to operate inside and outside the boundaries of their neighborhood on a daily basis, are not necessarily dedicated to a single place, and have differing definitions of what their neighborhood is over time (Lees et al., 2007). Nonetheless, scholars agree that census tracts come close to the definition of a neighborhood and are sufficient for understanding neighborhood correlates (Crowder and Downey, 2010).

[9] The ACS 2010-2014 5-Year estimates would have been ideal for these estimates as they overlap with the 2013 UDs. However, these data do not have a table with complete racial breakdowns of householders by race, only partial racial breakdowns. Therefore, I use the 2010 Decennial census data to uniformly calculate the breakdown of race, sex, and the combination of race and sex. Furthermore, the racial estimation in the Bayes model uses the 2010 Census neighborhood composition to predict race of individuals. Therefore, using the 2010 data on both individual and combined neighborhood demographic estimations seems to be the best practice. All other neighborhood economic and racial characteristics in the proceeding results use the 2010-2014 5-year ACS estimates because they overlap with the 2013 year from which the evictions were collected.

Regional Subsets

Eviction rates among sub-regions of King County, WA may vary as each area may be experiencing differing socioeconomic and market trends. I divide King County into four key sub-regions: Seattle, East King County, South King County, and other regions that include low-population areas of far east King County along the Cascade Mountain range and Vashon Island in west King County in the Puget Sound. Tracts within the Seattle city limits are experiencing some of the highest increases in housing costs in the nation (Fowler, 2016). Evidence suggests that this process has been displacing Seattles low-income and non-White residents from traditionally minority neighborhoods to even poorer and less advantaged tracts in South King County (McGee, 2007). In return, even poorer residents living in South King County may face higher threats to evictions as increasing population coincides with competition for existing housing. Research suggests that evictions may increase when gentrification and population increases occur (Formoso et al., 2010). East King County holds the cities of Bellevue and Renton, home of the tech giant Microsoft and local startups. These areas have a higher White and Asian population and higher incomes as compared to South King County. Evictions should be somewhat low on the East side as there is ample housing and a diverse rental market across the area.

Neighborhood Racial Typology

To explain neighborhood racial dynamics associated with the distribution of eviction rates, I utilize a modified version of the neighborhood racial typology used by Hall, Crowder, and Spring 2015 for White, Black, Asian, and Latino residents in King Countys tracts. I begin with sixteen neighborhood types: all White (>90% White); mostly Black (>70% Black); mostly Asian (>70% Asian); mostly Latino (>70% Latino); White-shared (<90% White and all other groups <10%); six two-group types (e.g., White-Asian with 10 to 90% White, 10 to 70% Asian, and all other groups <10%); four three- group types (e.g., White-Black-Asian where the three groups are >10% and

Latinos are <10%); and integrated White-Black-Asian-Latino (all groups are >10%).

These sixteen categories are collapsed into eight types to accommodate King Countys distinctive racial composition (e.g., there are no mostly Black tracts) and consolidate types with only a few cases into appropriate types for analysis. This results in the following 8 neighborhood types: all White; White-shared (mostly White with all other groups <10%); White-Asian; White-mixed (all three-group types that included Whites >10%); White-Black; White-Latino; integrated; and mostly minority (<20% White).

There may be varying consequences for integrated and segregated neighborhoods (hypothesis 2). Diverse neighborhoods may see more evictions as a result of housing competition between Whites and non-Whites. Gentrification theory posits that middle-class Whites may move into historically minority areas, where residents have endured more financial and material hardships over time, to find affordable housing. Subsequent increases in rent due to market competition then forces lower- income households to move out (Lees et al., 2007). Thus, integrated areas may see a higher rate of evictions among minorities. Segregated White neighborhoods may see lower eviction rates while more minority shared, or minority dominant, areas may see the opposite.

Neighborhood Economic & Housing Market Characteristics

To understand the association of household economic conditions within a neighborhood, I use rent burdenthe proportion of households using more than 30% of their income towards rentto capture socioeconomic disadvantage related to eviction concentrations (hypothesis 3). Two key structural constraints found among the evicted is high housing costs and stagnant wages (Desmond, 2012). Higher levels of rent-burden among tenants forces them to make difficult decisions between allocating their limited income towards rent or basic necessities such as food, transportation, or health, among other essentials (Desmond and Kimbro, 2015; Holupka and Newman, 2012; McConnell, 2012). Furthermore, most evictions are due to delinquent payments (Brophy and Smith, 1997;

Desmond, 2012). Therefore, the proportion of those facing rent burden in a neighborhood may help explain the interlinking mechanism of low-income and housing costs, where higher rent burdens in a tract should be positively related to higher rates of eviction. As the housing market plays an important role in determining where tenants can live, this trend may play an important role in the concentration of evictions. To account for this, neighborhood median rent (hypothesis 4) and rental vacancy rates are controlled to analyze increasing housing costs (Desmond, 2012) and rising housing insecurity (Dwyer and Phillips Lassus, 2015). Rent burden and vacancy rate are taken from the ACS 5-year estimates of 2010 to 2014 while rent data is drawn from the 2013 estimates of overall tract level median rent from Zillow. Zillows rent estimates (Rent Zestimates) are calculated using monthly rental listings and nearby housing variables (e.g., home values, tax assessments, and location) to predict the rental value for the given year (Bun, 2012). The ACS collects rental data biannually among a sample survey of households. Compared to ACS 5-year estimates for 2010-2014, Zillow rents are on average 51% higher. Given the relative frequency and breadth of rental property variables collected within Zillow data, this is a preferable data source.

2.5 Results

2.5.1 Eviction Counts

Since 2004, the number of UDs in King County has declined, topping out at 7,030 cases in 2005 and dropping to 5,225 cases in 2013 (Figure 2.1 - left), an average of just over 14 eviction cases per day. The first clue for possible racial disparities in unlawful detainers draws from the disparate renting rates within each racial group (Figure 2.1 - right). King County‘s population (red bars) is mostly White (63%), followed by Asian (15%), Latino (9%), and Black residents (6%). Among renters, Black households rent at a rate nearly two times higher than White households (57% versus 30% respectively) resulting in a higher exposure to unlawful detainers for African Americans.

Among the counts of UD individuals and households in King County (Table 2.2), White and

Black UDs are the most represented among all racial groups. For Whites, there are a total of 3,674 individuals and 2,642 households (52% for both). Among Black residents, there are 2,071 individuals (29%) and 1,590 households (31%). While the count of unlawful detainers is higher for Whites, the rates of unlawful detainment among Black defendants is four times greater than it is for Whites. This is because the Black to White population ratio is 0.09, while the Black to White unlawful detainment rate is 1.66. This means that a much higher proportion of Black renters face unlawful detainment than do Whites.

2.5.2 Evictions by Race & Sex

Group specific rates and rate ratios[10] are constructed from race, sex, and combined race and sex groups for unlawful detainers (numerator) and renter householders in King County (denominator). Figure 2.2 shows the percentage rates of UDs (red bars) for all households; by sex; by racial groups for White, Black, Latino, Asian, and non-White (all three minority groups combined minus Whites); and combined race and sex. The rate ratios (teal bars) show the rate ratio of unlawful detainer rates for the given group versus the opposite sex or White respective group (e.g., female to male, Latino to White, Black male to White male, Black female to White female, etc.).

In 2010, there were 322,514 renting households and 5,111 (1.58%) UD households in 2013. Within the sex category, females (rate of 1.82%) were evicted at a ratio 32% more than males (rate of 1.38%). Between racial groups, Black renters faced the highest rate of UDs at 5.12%, followed by Latinos (1.85%), Whites (1.3%), and Asians (0.77%). As compared to Whites, the rate ratio of Black UDs is nearly four times higher (3.94) and 1.42 times higher for Latinos. The overall eviction rate for non-Whites (Black, Latino, and Asian) was 60% higher than for Whites.

---

[10]Rate ratios, a more conservative measure, are preferred over odds ratios (or risk ratios) because the eviction records come from 2013 while household data come from 2010. Had the household and eviction data overlapped in years, risk ratios would be more appropriate. Rates place the events in the numerator and the exposure group in the denominator ($\frac{evicted}{renters} = rate$) while odds would divide evicted over non-evicted ($\frac{evicted}{renters-evicted} = odds$)

Combining race and sex of householders, Black female headed households had the highest rate of UDs (6.36%) followed by Black male heads (4.06%), Latino female heads (1.98%), Latino male heads (1.73%). The overall non-White female headed household UD rate was 2.49% while the male non-White head rate was 1.72%. Among Whites, female heads were evicted 23%

more (1.44%) than males (1.17%). Comparing the respective sex category to Whites, Black female heads were evicted at a rate 4.42 times more than White females. Black male heads were evicted 3.46 times more than White male heads. Latino male heads were evicted 1.48 times more than White male heads and Latino females were evicted 1.37 times more than White female heads. Using Table 2.3, one can customize the rate ratios by dividing the rates of any two groups to find the given ratios. For example, the rate ratio of Black female headed households compared to White male headed households is $\frac{6.36}{1.17} = 5.44$.

Figure 2.3 displays the geographic distribution of the eight neighborhood racial typologies overlaid by unlawful detainer locations. Most UDs fall within the South King County (57%) and Seattle (27%) regions (see Table 2.4 for regional counts). South Seattle and South King County hold the majority of White-Latino, White-Black, and integrated neighborhoods. East of Seattle lies the cities of Bellevue and Redmond, home of Microsofts main campus, with mostly White-Asian neighborhoods. Further east lies the Cascade mountain range, a low population area with mostly White and White-shared tracts. The racial breakdown of UDs by region (Figure 2.4) shows South King County has the highest rates of eviction, with Black households leading (7.1%) followed by Latino (2.3%), White (1.9%), and Asian (1.4%). Seattle has the second highest rates where Black households have the highest rates again (2.8%), and all other racial groups at or below 1%. The remaining regions, have relatively low rates of eviction overall, hovering around 1%.

2.5.3 Neighborhood Racial Typology

Examining the racial typology of the 397 tracts in King County (Table 2.5), White-Asian tracts are the most prominent with 127 (mostly White with >10% Asian) followed by 103 White-shared (mostly White with all non-White groups <10%), 84 White-mixed (mostly White but more than one non-White group is >10%), and 29 integrated (all groups >10%). Seattle consists mostly of White-shared, White-Asian, White-mixed, and most of the mostly minority tracts. The South King County has a larger non-White population with the majority of integrated neighborhoods, White-mixed neighborhoods, and most of the White-Latino shared tracts. On the east side is the city of Bellevue where the majority of White-Asian tracts are located. Further east, towards the Cascades, lies mostly all White and White-shared tracts.

From table 2.5 we see that the highest overall rates of contested evictions occur in White-Latino tracts (rate of 2.9% with 539 evictions for 18,462 renting households), integrated (2.8% with 921 evictions for 33,216 renting households), White-mixed (2% with 1,626 evictions for 80,573 renters), and mostly minority tracts (1.8% with 127 evictions for 7,171 households). The lowest rate of evictions occurs in White-shared (0.7% with 533 evictions for 76,002 households) White-Asian tracts (1% with 1,185 for 113,613 households), all White (1.2% with 35 evictions for 2,879 households), and White-Black (1.2% with 145 evictions for 12,188 households).

Figure 2.5 shows the disaggregated racial rates of evictions by neighborhood type. In tracts with >10% minority representation, Black households are evicted, on average, 4.2 times more than Whites, with rate ratios topping out at 6.5 and 9 times more than Whites in integrated and mostly minority neighborhoods, and between 2 and 3.5 times higher than the next highest evicted group in the respective neighborhood. The highest rate for Black household evictions is within integrated neighborhoods with a rate of 7.2% followed by White-Latino neighborhoods (5.5%) and White- mixed (5.0%). Latino householders have the second highest rates of evictions with the same top three neighborhood types (2.0%, 2.2%, and 1.9% respectively). Whites have the third highest rates (highest at 2.7% in White-Latino neighborhoods) while Asian householders have the lowest rates across neighborhoods (highest rate is 1.4% in White-Latino neighborhoods).

2.5.4 Neighborhood Rent Burden

Figure 2.6 shows the racial distribution of rent burden (the percent of the population contributing >30% of their income to rent) broken into six standard deviation categories ranging from less than -2 to greater than +2 standard deviations for King County. Again, Black households have the highest rates of UDs, but only in tracts greater than -2 standard deviations (>19% of the population facing rent burden). No Black or Latino households lived in the lowest rent-burden neighborhoods. Their rates increase from 2.3%, peaking at 5.4% between 0 and 1 standard deviation, then dropping to 1.9% in the end. Latino households come second with the highest rate (2.6%) found in the 1 to 2 standard deviation tracts. Whites, on the other hand, have a relatively steady, and low, increasing from 0.8% to 1.4%. Aside from Black households, other racial groups seem to see a steady increase in eviction rates as rent-burden increases (see Table 2.6 for full counts).

2.5.5 Housing Market

Figure 2.7 highlights the standard deviations of Zillows median rental estimate for 2013 by race. In the three lowest rental categories, Black households, again, take the highest rates of UDs. However, the average 2.5 Black to White rate ratio among the first three categories is unexpectedly high. What is particularly alarming is that over 87% of Black rental households live in the first two rental categories. In comparison, over 90% of Latino renting households live in the first two rental categories, but have much lower UD rates at 2.6 and 1.7, respectively. It is unclear to what extent the difference in Black and Latino evictions may be due to either lower contested evictions, or possibly a higher count of non-contested evictions for Latinos that are not captured in the data (see Table 2.7 for complete counts).

Figure 2.8 highlights the neighborhood vacancy rate for each racial category broken into four standard deviation categories. Once again, Black households have the highest rate overall, topping out at 6%, with rates 2.3 to 4.3 times higher than Whites across all groups. Among all other groups, there is a slight increase in evictions as vacancy increases, except in the final category where White, Asian, and Latino vacancies slightly decrease. This finding is counter to hypothesis 3b that vacancies are negatively related to evictions. Investigating tracts on a map shows that most of the high vacancy areas are located in South King County along with higher clustering of Black evictions (see Table 2.8 for full counts).

2.6 Conclusion

While recent research has highlighted the significant role that evictions play in the reproduction of urban poverty at the individual level, lack of cross-metropolitan data and demographic detail has limited detailed racial disparities and examinations of related neighborhood dynamics that might be associated with, or even driving, evictions. Utilizing new methods in race and sex estimation on new data from King County, WA, this analysis examines the individual-level and ecological-level of contested evictions. Results confirm that, like in prior research (Desmond, 2012), women have higher rates of evictions as compared to men, with extraordinarily high rates of contested evictions among Black householders. Female-headed households are evicted 32% more than men, with Black-female headed unlawful detainer rates at 4.42 and 5.44 times higher than White women and White men. Overall, Black and Latino householder eviction rates are 3.94 and 1.42 times higher than Whites.

Evaluating the ecological dynamics of contested evictions, neighborhood racial and economic compositions show several disparate relationships across different racial groups. The greatest concentration of overall evictions fall largely within the countys most diverse neighborhoods, with the highest rates (between 2% to 2.9%) within White-mixed, integrated, and White-Latino neighborhoods. Across all neighborhood racial typologies, Black households face extremely high rates of evictions wherever there is a substantial representation. Among the top three are the previously mentioned integrated, White-Latino, and White-mixed neighborhoods, where they lead all other groups with UD rates of 7.2%, 5.5%, and 5%. In integrated and mostly minority neighborhoods, they are evicted over 6 and 9 times more than Whites. Latinos come second in eviction rates, but still fall about 2/3rds below the rates of Black evictions. Basically, if there is a Black renting population within a King County tract, they face a disproportionately higher rate of evictions that other racial groups.

As the proportion of the population facing rent burden increases, so do eviction rates. Overall rates in neighborhoods with more than 32% of the population facing rent-burden range between 1.1% to 2%. However, Black household trends go well above all other groups with rates ranging from 1.9% to 5.4%. On average, Black households are evicted 3 times more than Whites, with the Black/White rate ratios reaching around 4 within tracts that fall between -1 and +1 standard deviations (68% of the tracts). Latino Households come in second with rates of 1.2% to 2.6% but only reach a rate ratio of 1.85 to Whites.

Within the context of neighborhood housing market drivers, evictions are lower when rent is higher. Black households are evicted 7.3% and 4.8% of the time in the lowest median rent neighborhoods (between \$1,000 and \$2,000), which is almost three times more than Latinos and almost four times more than Whites. Increases in vacancy rates also coincide with increases in overall evictions except, again, for Black households who see a relatively high rate of evictions regardless of the vacancy ratebetween two and three times higher than Latinos and over two and four times higher than for Whites.

One of the more puzzling findings in this analysis is the negative relationship of rent on evictions. One explanation may be that lower-rent neighborhoods may be less desirable due to some type of structural deficiencies, high turnover, or just simply being less attractive locations. However, the rapidly rising housing costs across the county may make these affordable areas more scarce and desirable, and therefore, motivate landlords to clear space for higher earning households. Given this metro level effect and the scarcity of affordable places, these spaces may be the last affordable space in the region, and therefore low-income households may fight harder to stay past the eviction deadline as there are few affordable spaces in the county that they can move too. Future research would require individual level data including income and purpose of eviction to reveal whether this really is the case or not.

Across all the results, Black households have excessively high rates of evictions above and beyond the average levels for any other group. This finding, in conjunction with the fact that Black renting rates are twice that of Whites, reinforces the point that Black households face high housing insecurity risks. These disparities reflect broader themes in historical and contemporary housing discrimination where segregation patterns and exclusion from loans have relegated Black households to live in more disadvantaged neighborhoods while being denied participation in the building of the middle class through homeownership.

The high rate of unlawful detainers among Black households in integrated and White-mixed neighborhoods is particularly troublesome, which raises questions on the assumption that diversity improves non-White household outcomes. This may be in part due to the consequences of gentrification in Seattle neighborhoods that have led to a large displacement of Black householders to poorer tracts in South King County (McGee, 2007). Figure 2.9 highlights the change in the location of Black residents over 40 years from highly segregated neighborhoods near downtown Seattle in 1980 to their diffusion towards the modern diverse neighborhoods in South King County that were formally all-White farm lands. However, it is difficult to understand why the rate of evictions among Black households in South King County are so much higher than in Seattle (7.8% versus 2.8%). It is possibly a social control or discrimination effect is occurring in South King County, targeting Black households as heterogeneity increases punitive evictions. Or, it could be a selection issue where lower-income Black households are moving to these spaces and being evicted more. Future research should disentangle this issue by disaggregating race specific economic characteristics of Black households in Seattle versus South King County.

The results from rent-burden also pose an interesting question regarding Black household eviction rates. It is understandable that higher rent-burdened neighborhoods would see higher rates of eviction due to the presence of higher economic insecurity. However, the significantly higher rates for Black tenants suggest that there is something else at play. One explanation is that Black households may largely be poorer than other households. Whites in King County have a median household income of around \$80,000 while the Black median household income is \$38,000. HUDs definition of low-income starts around \$64,000 for a family of four in 2013 King County and reaches extremely low-income status at \$26,000. However, the history of residential exclusion is largely a discriminatory effect, meaning we cannot pin this solely on economics. Future research should disentangle this trend and examine possible mechanisms that would explain this disparate rate as aggregate median income at the county level only scratches the surface of broader racial disparities in evictions.

The focus of the next chapter is to disentangle some of these findings using regression models on both local and extra-local predictors of eviction. Does the racial composition of the neighborhood matter more than the local housing market? Or, are eviction concentrations simply related to local income disparities or poverty? And, how might nearby economic and housing market conditions influence local rates of eviction? These questions are informed by theories of neighborhood racial stratification and housing markets at the local level while also examining the broader contexts of the metro and nearby neighborhoods.

Table 2.1: Differences in Evictions Between Single and Multiple Persons in a Household

	All Ev.	All Ev. Rate	Single Ev.	Single Ev. Rate	Mult. Ev.	Mult. Ev. Rate	Diff. All v. Sing.	Diff. Sing. v. Mult.
Asian female	212	0.03	70	0.02	142	0.04	0.01	-0.02
male	223	0.03	92	0.03	131	0.04	0.00	-0.01
Black female	1097	0.16	652	0.19	445	0.12	-0.03	0.07
male	928	0.13	490	0.14	438	0.12	-0.01	0.02
Latino female	404	0.06	149	0.04	255	0.07	0.01	-0.03
male	428	0.06	168	0.05	260	0.07	0.01	-0.02
Other female	1	0.00	1	0.00	–	–	-0.00	–
male	13	0.00	1	0.00	12	0.00	0.00	-0.00
White female	1805	0.26	847	0.25	958	0.26	0.01	-0.02
male	1822	0.26	910	0.26	912	0.25	-0.01	0.01

Table 2.2: Counts of Evictions in King County by Race and Sex

	Asian	Black	Latino	Other	White	Total
Individual	464 (6.6%)	2,071 (29.3%)	842 (11.9%)	14 (0.2%)	3,674 (52%)	7,065
Female	212 (6%)	1,096 (31.2%)	404 (11.5%)	1 (0%)	1,802 (51.3%)	3,515
Male	223 (6.5%)	928 (27.2%)	428 (12.6%)	13 (0.4%)	1,818 (53.3%)	3,410
Household	301 (5.9%)	1,590 (31.1%)	569 (11.1%)	9 (0.2%)	2,642 (51.7%)	5,111
Female Head	118 (5%)	816 (34.6%)	240 (10.2%)	1 (0%)	1,184 (50.2%)	2,359
Male Head	163 (6.1%)	740 (27.8%)	324 (12.2%)	8 (0.3%)	1,423 (53.5%)	2,658

Table 2.3: Rates of Evictions for sex Households & Race Households

	Renters (Tract Avg.)	Evicted (Tract Avg.)	Rate (%) (Tract Avg.)	Rate Ratio (Tract Avg.)
	All Households			
Households	322,514 (812.38)	5,111 (12.87)	1.58 (1.61)	
	Sex of Householder			
Male	193,077 (486.34)	2,658 (6.70)	1.38 (1.34)	
Female	129,437 (326.04)	2,359 (5.94)	1.82 (2.09)	1.32 (1.56)
	Race of Householder			
White	203,544 (512.71)	2,642 (6.65)	1.30 (1.47)	
Black	31,070 (78.26)	1,590 (4.01)	5.12 (2.63)	3.94 (1.79)
Latino	30,839 (77.68)	569 (1.43)	1.85 (1.33)	1.42 (0.90)
Asian	39,196 (98.73)	301 (0.76)	0.77 (1.02)	0.59 (0.69)
Non-White	118,970 (299.67)	2,469 (6.22)	2.08 (1.41)	1.60 (0.96)
	Race & Sex of Household Head			
White Male	121,322 (305.60)	1,423 (3.58)	1.17 (1.22)	
Female	82,222 (207.11)	1,184 (2.98)	1.44 (1.94)	
Black Male	18,241 (45.95)	740 (1.86)	4.06 (2.07)	3.46 (1.69)
Female	12,829 (32.32)	816 (2.06)	6.36 (3.36)	4.42 (1.73)
Latino Male	18,687 (47.07)	324 (0.82)	1.73 (1.24)	1.48 (1.02)
Female	12,152 (30.61)	240 (0.60)	1.98 (1.52)	1.37 (0.79)
Asian Male	24,166 (60.87)	163 (0.41)	0.67 (0.96)	0.58 (0.78)
Female	15,030 (37.86)	118 (0.30)	0.79 (0.94)	0.54 (0.49)
Non-White Male	71,755 (180.74)	1,235 (3.11)	1.72 (1.19)	1.47 (0.98)
Female	47,215 (118.93)	1,175 (2.96)	2.49 (1.70)	1.73 (0.87)

Data: 2010 US Decennial Census and King County Unlawful Detainer Data 2013.

Table 2.4: Regional Unlawful Detainer Variation by Race

	Regional Percent	UD Rate (Count)	White Rate (Count)	Black Rate (Count)	Asian Rate (Count)	Latino Rate (Count)
Seattle	26.6%	0.9% (1358)	0.7% (762)	2.8% (410)	0.4% (77)	1.0% (106)
South	57.6%	2.8% (2943)	1.9% (1209)	7.1% (1161)	1.4% (164)	2.3% (403)
East	15.2%	1% (777)	1.1% (639)	0.6% (19)	0.4% (59)	0.9% (60)
Other	0.6%	1.3% (33)	1.4% (32)	–	1.4% (1)	0.0% (0)

Table 2.5: Evictions by Neighborhood Racial Type

Neighborhood Type (count)	Total Ev.	Total Renters	Total Rate (%)	White Rate (%)	Black Rate (%)	Asian Rate (%)	Latino Rate (%)
All White (11)	35	2,879	1.2	1.3	—	0.0	0.0
White-Shared (103)	533	76,002	0.7	0.8	0.3	0.3	0.5
White-Asian (127)	1,185	113,613	1.0	1.1	2.6	0.4	1.3
White-Mixed (84)	1,626	80,573	2.0	1.4	5.0	0.8	1.9
White-Latino (24)	539	18,462	2.9	2.7	5.5	1.4	2.2
White-Black (10)	145	12,188	1.2	0.7	3.7	0.8	1.3
Integrated (29)	921	33,216	2.8	1.1	7.2	1.1	2.0
Mostly Minority (9)	127	7,171	1.8	0.4	3.6	0.8	1.5

Table 2.6: Racial Differences in UD Rates by Rent Burden and Race

Standard Deviation (Percent in Rent Burden)	Total Renters	UD Rate	White Rate	Black Rate	Asian Rate	Latino Rate
<-2 SD (<18%)	1,887	0.7%	0.8%	—	0.8%	—
-2 to -1 SD (19% - 32%)	40,653	0.9%	0.9%	2.3%	0.4%	1.0%
-1 to 0 SD (32% - 45%)	132,944	1.1%	1.0%	3.7%	0.5%	1.2%
0 to 1 SD (45% - 58%)	107,738	1.9%	1.3%	5.4%	0.8%	1.6%
1 to 2 SD (58% - 70%)	57,357	2.0%	1.4%	4.9%	0.8%	2.6%
>2 SD (72% - 76%)	3,525	1.4%	1.4%	1.9%	0.5%	1.5%

Table 2.7: Racial Differences in Unlawful Detainer Rates by Median Rent and Race

	All	White	Black	Asian	Latino
$1.0k to $1.4k (<-1 SD)					
Renters	24,971	14,774	3,689	3,302	4,530
Unlawful Detainers	724	296	270	42	116
Rate	(2.9%)	(2.0%)	(7.3%)	(1.3%)	(2.6%)
$1.4k to $2k (-1 to 0 SD)					
Renters	205,429	131,292	25,986	27,945	23,960
Unlawful Detainers	3,618	1,752	1,249	210	398
Rate	(1.8%)	(1.3%)	(4.8%)	(0.8%)	(1.7%)
$2.0k to $2.5k (0 to 1 SD)					
Renters	93,206	70,143	4,014	12,876	5,493
Unlawful Detainers	637	485	68	38	46
Rate	(0.7%)	(0.7%)	(1.7%)	(0.3%)	(0.8%)
$2.5k to $3k (1 to 2 SD)					
Renters	14,279	11,025	430	2,157	734
Unlawful Detainers	81	68	2	7	4
Rate	(0.6%)	(0.6%)	(0.5%)	(0.3%)	(0.5%)
$3.0k to $5k (>2 SD)					
Renters	6,084	4,951	211	697	343
Unlawful Detainers	51	41	1	4	5
Rate	(0.8%)	(0.8%)	(0.5%)	(0.6%)	(1.5%)

Table 2.8: Racial Differences in Unlawful Detainer Rates by Vacancy Rates and Race

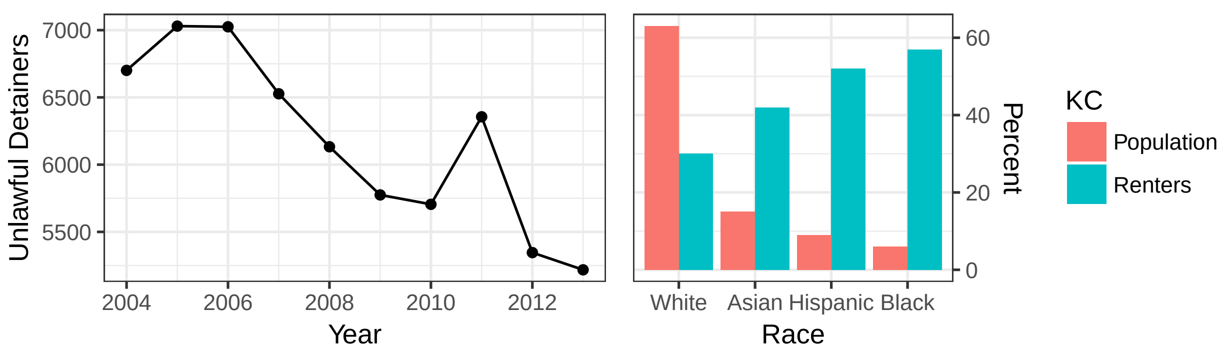
	All	White	Black	Asian	Latino
0% to 4% (-1 to 0 SD)					
Renters	200,302	138,592	17,015	27,352	18,433
Unlawful Detainers	2,285	1,289	641	134	216
Rate	(1.1%)	(0.9%)	(3.8%)	(0.5%)	(1.2%)
5% to 8% (0 to 1 SD)					
Renters	104,574	67,721	12,355	15,401	11,503
Unlawful Detainers	1,881	848	690	118	223
Rate	(1.8%)	(1.3%)	(5.6%)	(0.8%)	(1.9%)
8% to 13% (1 to 2 SD)					
Renters	30,326	20,395	3,280	3,524	4,102
Unlawful Detainers	732	421	158	40	111
Rate	(2.4%)	(2.1%)	(4.8%)	(1.1%)	(2.7%)
13% to 26% (>2 SD)					
Renters	8,902	5,532	1,680	751	1,022
Unlawful Detainers	213	84	101	9	19
Rate	(2.4%)	(1.5%)	(6.0%)	(1.2%)	(1.9%)

Table 2.9: Housing Justice Project Yearly Counts

Year	Number of Cases	Women	Men	Asian	Black	Latino	White
2015	1782	938	696	58	572	149	671
2014	1755	866	656	36	437	132	582
2013	1582	865	632	51	485	122	615
2012	1586	872	658	58	538	115	600
2011	1670	893	691	75	531	105	664
2010	1793	938	786	78	519	129	727
2009	1630	861	714	82	487	130	617
2008	1590	903	682	87	522	106	670
2007	1396	779	617	52	429	85	619
2006	1322	748	574	52	410	69	519
2005	1006	564	442	32	291	52	383

Data: Housing Justice Project, 2016.

Figure 2.1: King County, WA Unlawful Detainer Count, Population, and Renters.



Unlawful detainer cases 2004-2013 (left) and King County population and renter distribution ACS 2010-2014 (right).

Figure 2.2: Evictions by Household Demographics.

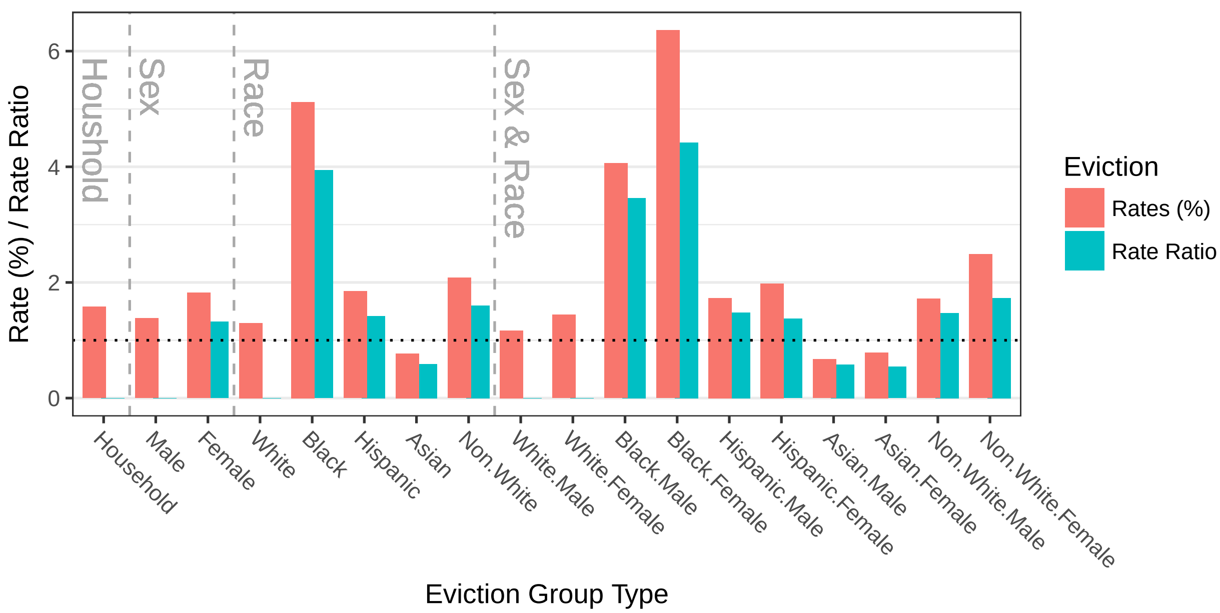


Figure 2.3: Spatial Distribution of Evictions and Neighborhood Racial Typology.

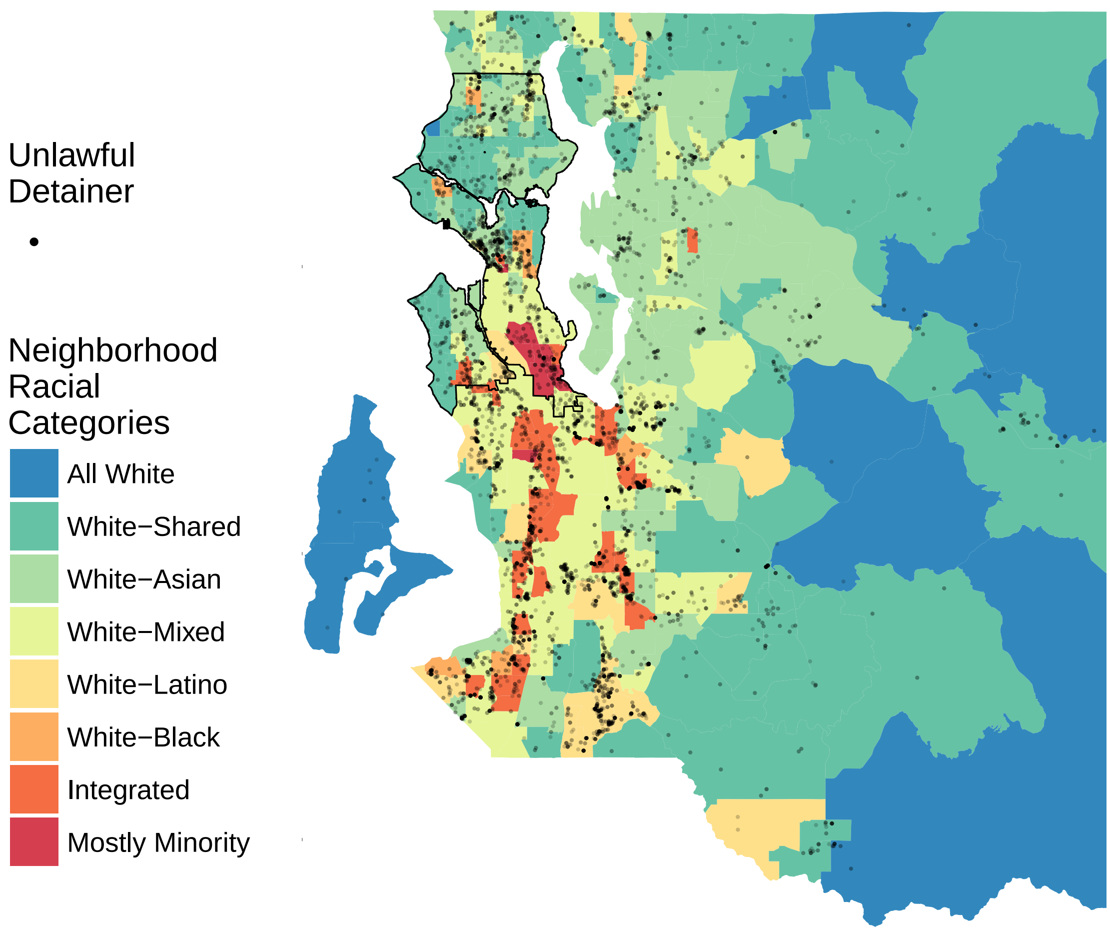


Figure 2.4: Evictions by Race & County Region

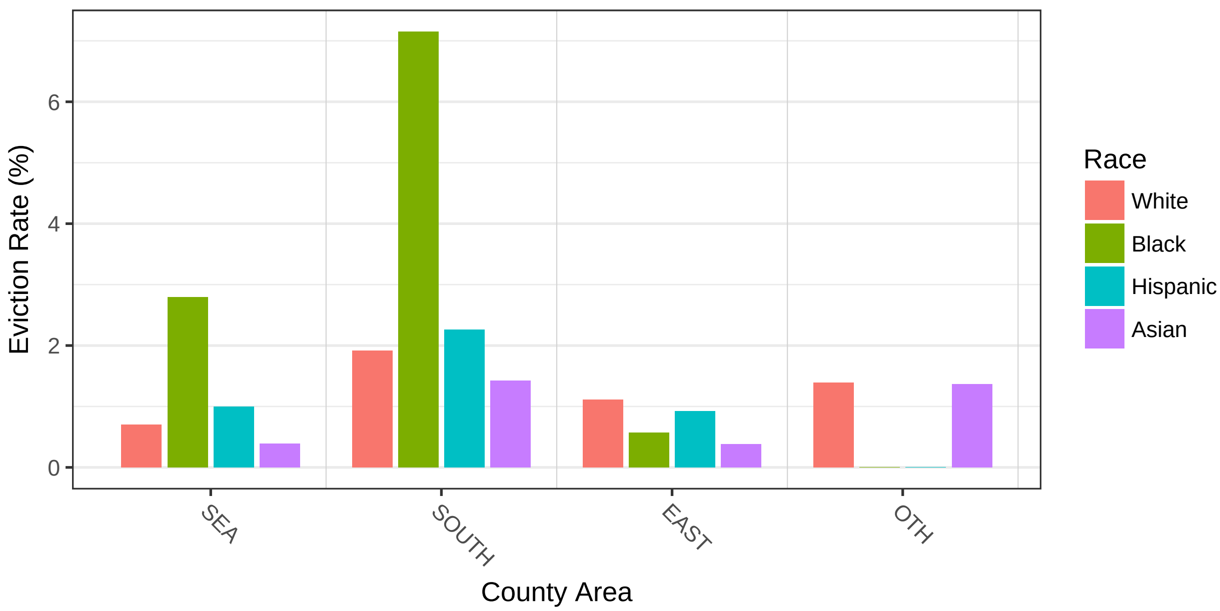


Figure 2.5: Racial Differences in Unlawful Detainers by Neighborhood Racial Types

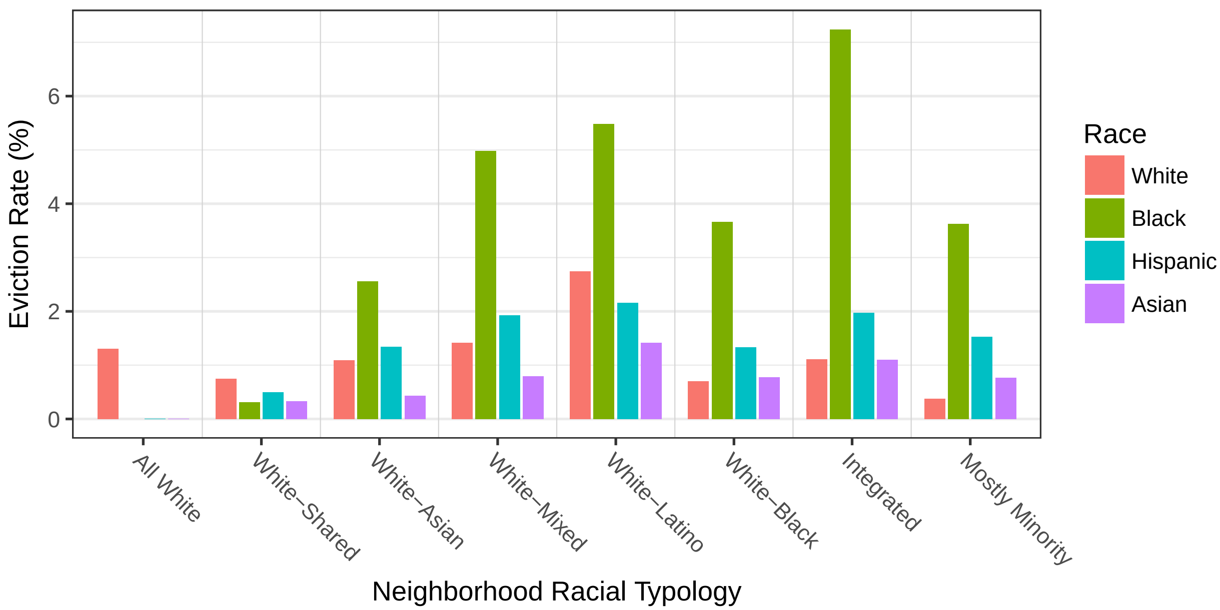


Figure 2.6: Evictions by Race & Proportion of Neighborhood Rent Burden

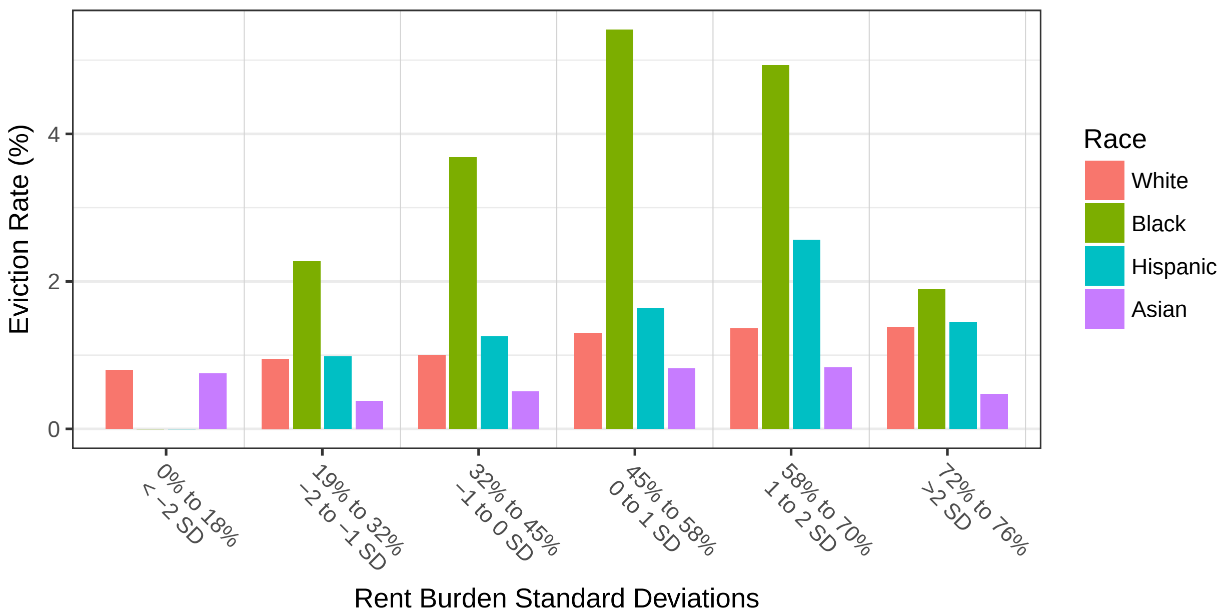
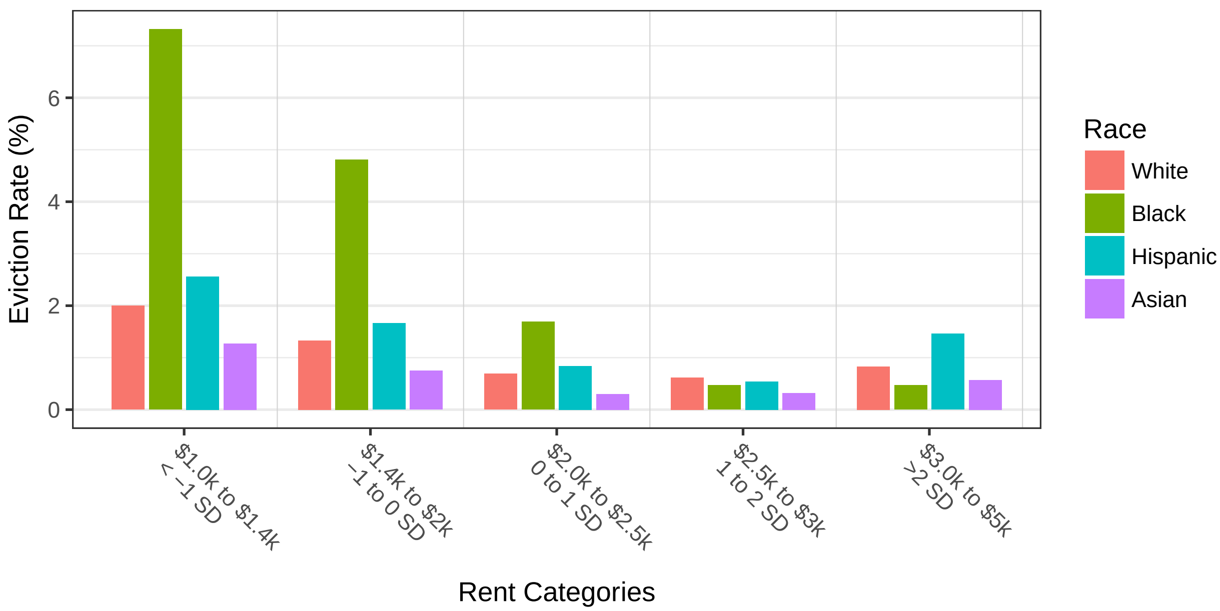


Figure 2.7: Evictions by Race & Median Rent



Data drawn from 2013 Zillow median rent estimates for all rental units at the tract level.

Figure 2.8: Evictions by Race & Vacancy Rate

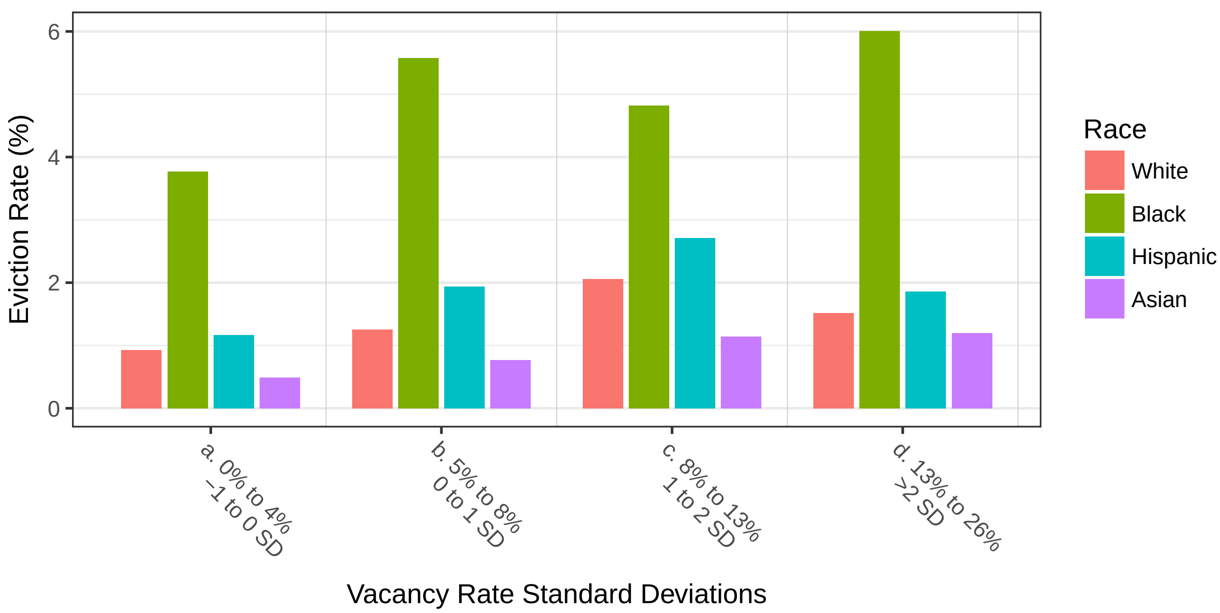
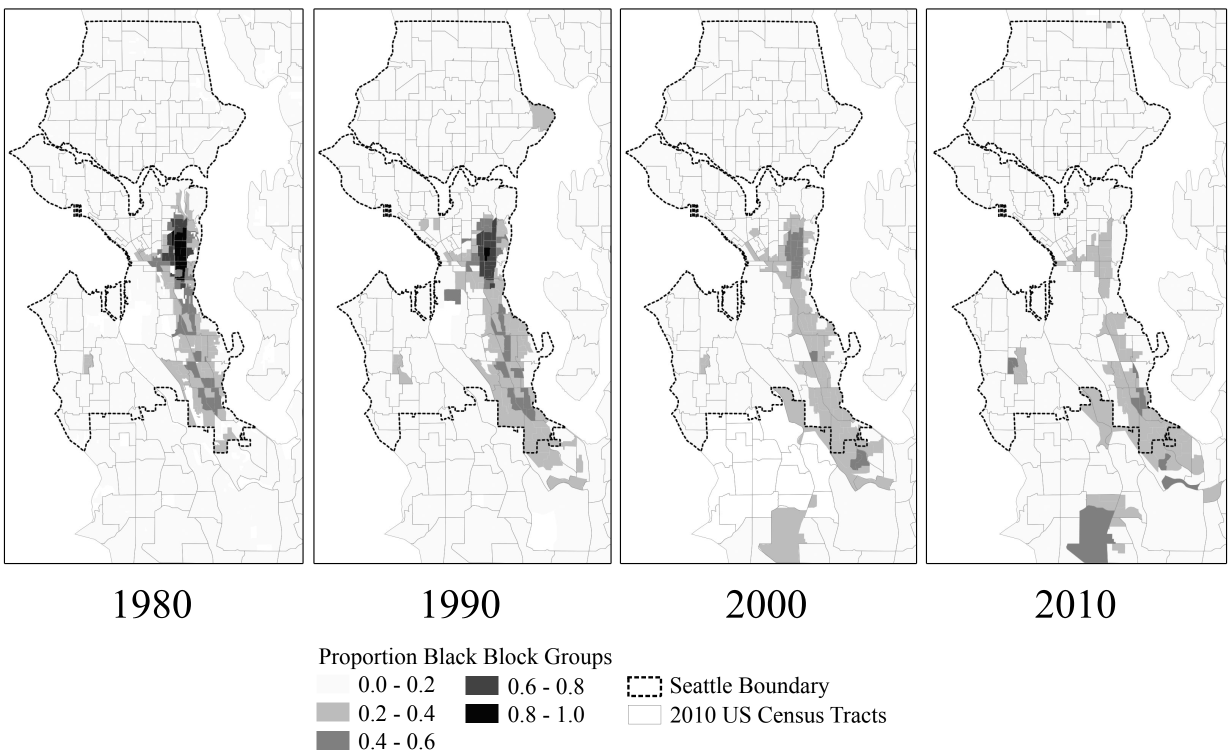


Figure 2.9: Change in Black Population 1980 to 2010



In 1980, there was a very segregated black population in Seattle's Central District. Through the years, this population as declined and moved south, even outside of the city limits. In 1980, some block groups had up towards 90% black block groups, whereas in 2010, the same block groups had less than 20% black.

Chapter 3

SPATIAL DYNAMICS OF EVICTIONS

3.1 Introduction

Emerging research on evictions sets out to understand the reasons and consequences of forced mobility among low-income renters (Desmond et al., 2015). Thus far, this area of study has focused mostly on individual-level and household-level characteristics that lead to forced removal, identifying the key structural constraints of stagnant wages and welfare among low-income households that cannot match steadily increasing rents (Desmond, 2012). However, little work has been done to understand neighborhood level associations that not only drive the rental market, but also social stratification among households.

The consequences of an eviction have long-lasting penalties that prevent households from achieving suitable housing in decent neighborhoods and is tied to persistent hardships and poverty (Desmond and Bell, 2015; Desmond and Kimbro, 2015; Desmond and Shollenberger, 2015). This research is important given that housing insecurity in the US is growing with no expectation of slowing down in the coming decades (Dwyer and Phillips Lassus, 2015; Enterprise Community Partners, 2016).

One facet of evictions that needs attention is the metropolitan and neighborhood level associations and drivers. Neighborhood research reinforces how place matters when it comes to household opportunities, residential mobility, concentrated poverty, health, crime, and overall family outcomes (Charles, 2003; Dwyer and Phillips Lassus, 2015; Krysan et al., 2015; Sampson et al., 2002; Sharkey, 2008; South and Crowder, 1997). The few studies that have examined spatial connections tied to evictions find that most evictions occur in lowest rent, minority, and disadvantaged neighborhoods (Desmond and Gershenson, 2017); evidence that segregation and concentrated poverty play a large role in this life event. While White neighborhoods and households also see their share of evictions, non-Whites still experience high rates of eviction in these spaces (Desmond, 2012); suggesting broader racial disparities among the evicted. Furthermore, contemporary shifts in metropolitan economies and housing markets may increase evictions in, or near, diverse and rent-burdened neighborhoods as wealthier households seek new destinations for their affordability, leading to increased housing costs through heightened demand, and subsequent pricing out of low-income tenants (Atkinson, 2002; Hwang and Sampson, 2014; Maly, 2005; Smith, 1996). Prior research that controls for gentrification finds no significant effect net of other local variables, individual SES, family structure, and network ties (Desmond and Gershenson, 2017). However, this analysis has been confined to a rust-belt city where there may be lower levels of gentrification and overall greater levels of poverty, minority representation, and racial segregation.

Would these findings still hold in other metros with lower segregation? Does the racial composition of the neighborhood matter more than the local housing market? Or, are eviction concentrations simply related to local income disparities or poverty? And, how might nearby economic and housing market conditions influence local rates of eviction?

In this chapter, I investigate the ecological dynamics of evictions associated with local and extra-local neighborhood dynamics in King County, WA. Using spatial data analysis on the tract level concentrations of unlawful detainer court records, neighborhood-level racial and economic compositions from the 2011-2015 ACS, and rent data from Zillow, I address several interrelated questions: (1) To what extent does neighborhood socioeconomic status relate to eviction rate among low-income households? (2) How does the local rent and racial composition relate to the rate of evictions? (3) And, finally, do the extra-local dynamics of these variables have a greater effect on evictions than the local neighborhood dynamics? Driven by recent research on evictions and classic works on urban sociology, I test three main theoretical frameworks that center around the housing market, neighborhood stratification, and contested spaces to determine whether one or more of these frameworks may explain the geographic concentrations of evictions.

3.2 Theory

Prior research on evictions helps narrow down possible spatial dynamics that are related with the geographic concentration of evictions. First, the literature points out that the socio-demographic characteristics of the evicted are mostly minority, female, and low-income (Desmond, 2012). The leading cause of eviction is falling behind on rent due to rent-burden where most families that are contributing upwards of 90% of their income to housing costs (Desmond and Perkins, 2016). Given these economic constraints, most of these households are confined to the least expensive, highest poverty, and most disadvantaged neighborhoods in a city (Desmond and Gershenson, 2017). Despite its affordability, these neighborhoods still experience slow annual increases in rent that outpace minimum wage and welfare stipends that have not seen increases in decades (Desmond, 2012).

Second, economic growth in a city may spur market changes in affordable areas that threatens displacement through even faster rising rents (Aratani et al., 2011; Desmond and Gershenson, 2017; Dwyer and Phillips Lassus, 2015; Maly, 2005). Beyond the local areas, landlords may be influenced by nearby conditions, such as any changes in the rental market, new construction, and population growth, that may provide a forecast for local areas that might allow them to increase economic gains. For example, when a landlord owns a property in a high-poverty neighborhood, where there is little opportunity to replace low-income households with higher paying tenants, they tend to have softer restrictions on when, and who, to evict due to the trouble of replacing a tenant (Desmond and Gershenson, 2017). In addition, the cost of evicting a tenant would mean losing about one month's rent and any guarantee of recouping lost back-rent that the tenant may owe (Garboden and Rosen, 2017). However, with market growth in or near an area, the benefits of removal may outweigh the costs which may encourage landlords to go ahead and apply stricter guidelines on tenants falling behind on rent or breaking rules to make room for higher earning tenants (Byrne, 2003).

Third, the fallout of changing neighborhoods is further complicated as evidence suggests there is an overall higher rate of eviction among poor Black and Latino households (Desmond, 2012). Therefore, changes from poor segregated neighborhoods to integrated neighborhoods may see a higher rates of evictions among low-income Black or Latino households as they may have a more difficult time competing with increasing rents in the area and any discriminatory biases that may force them to move out of the community (Desmond et al., 2015).

To simplify and unpack these complexities, I pose three theoretical frameworks on the neighborhood market, economic, and racial compositions. The intention of these frameworks is to try and isolate which ecological effects may be contributing most to eviction concentrations at the neighborhood-level (not the individual-level). These theories compare variables in both local and extra-local neighborhood contexts. The first two frameworks focus on the housing market and racial composition at the local level while the third frameworkthe contested spaces theoryfocuses on the extent to which extra-local neighborhood characteristics are associated with local eviction rates.

3.2.1 The Neighborhood Housing Market Framework

The first framework revolves around the neighborhood market conditions that would contribute to pressures on household-level economics where the geographic concentration of evictions is related to neighborhood-level costs of housing. In its simplest form, this theory tests whether neighborhood rent and poverty contribute to the geographic concentration of evictions inside the focal neighborhood.

Two main factors are at play within this theory. First, given that falling behind on rent is a leading cause for an eviction, neighborhood level rent and poverty may explain local rates of eviction. The rental market, by its very nature, demonstrates the demand of an area, where places are commodified and its cost is matched to the demand and desirability of the area (Logan and Molotch, 1987). High rent neighborhoods tend to have some innate, desirable feature about them that sanctions the high cost of living there, whereas, low rent areas may have less desirable features that warrant its lower cost. For example, low poverty and proximity to an urban business district, or some other desirable aesthetic of a neighborhood, may increase its value whereas structural, social, and economic disadvantage may be less desirable and lead to lower rents. The income level of a household then determines whether a household can afford a low or high rent space. For extremely low-income households, the bulk of those that face contested evictions (Desmond, 2012), the most affordable areas are likely their only option. Yet, the structural constraints of stagnant wages and welfare stipends within the household still may not allow them to afford these low-cost areas. Furthermore, external pressures may make affordable areas difficult to maintain housing. Landlords may avoid evicting tenants if the likelihood of replacing them with higher-earning ones is low (Desmond and Gershenson, 2017). However, if affordability is a scarce commodity in a rapidly increasing housing market, such as the case for King County (McGee, 2007), then the lowest rent neighborhoods may be prime areas to replace low-income tenants with higher-earning ones seeking affordability and willing to ignore structural aversions. In addition, the scarcity of affordable spaces may inspire households to fight to stay given there are few places they can move to, thus leading to more legal forced evictions. Based on this market theory and the economic circumstance of the study area, contested evictions should be higher in more affordable spaces due to possible scarcity of affordable spaces.

Second, the higher level of poverty in a neighborhood should predict higher rates of eviction due to higher concentrations of lower-income households. With minimum wages and welfare stipends remaining stagnant over several years, rent-burden forces low-income households to devote larger portions of their income to housing expenses, even in high-poverty neighborhoods, while sacrificing essential needs such as food, medication, transportation, and education (McConnell, 2012; Newman and Holupka, 2014). Poor households facing high rent-burden are twice as likely to have been displaced through evictions as compared to all other groups (Newman and Wyly, 2006). Court surveys also show that 1/3rd of evicted households were devoting at least 80% of their income to rent (Desmond and Bell, 2015) and the highest rates of eviction occurring in high poverty neighborhoods, about 7.4% as compared to the metro average of 3.5% (Desmond, 2012). This suggests poverty has a positive relationship with evictions.

3.2.2 The Neighborhood Racial Stratification Framework

Eviction concentrations are highly racialized artifacts where a majority of tenants facing removal are Black and living in Black and diverse neighborhoods. This leads to the second framework that revolves around neighborhood racial stratification, which suggests that the geographic concentration of evictions should be higher in neighborhoods with moderate to high proportions of Black and Latino households. Court surveys in Milwaukee found that 74% of the defendants were Black and about 46% of evictions occurred in Black neighborhoods, 4% from Latino, and 30% from mixed. Even in White neighborhoods, where 20% of evictions occurred, Black and Latino households were evicted at levels that were 2.5 and 1.78 times greater than for White households (Desmond, 2012). However, research that controlled directly for race of the householder net of other socio-demographic and network characteristics found that race did not predict evictions. One explanation is that the analysis was conducted in the highly-segregated city of Milwaukee where landlords may have a difficult time replacing a, say, Black tenant with a White tenant in a Black segregated neighborhood (Desmond and Gershenson, 2017).

A possible explanation for the high minority representation in earlier studies is that Black and Latino households rent about 1/3rd and two times more than Asian and White households.

Therefore, Black and Latino tenants are de facto at a higher risk of eviction simply due to over-representative renting within their populations. This is due, in part, to historical exclusion from lending and access to better neighborhoods through discriminatory policies established by policymakers and banks (Conley, 1999; Oliver and Shapiro, 2006). These practices contributed to the spatial clustering of non-White households in specific areas that also face greater levels of economic disadvantage. Exposure to segregated spaces impedes economic and spatial mobility to better neighborhoods, undermines social and economic well-being, exposes vulnerable households to negative health and social problems, is associated with the reproduction of poverty, and is linked to high levels of residential instability (Charles, 2003; Massey and Denton, 1993; Peterson and Krivo, 2010; Sampson et al., 2002; Sharkey, 2008). Given that economic hardships are at the root of evictions, these spatial dynamics give way to higher rates of evictions for low-income households of color who are isolated in disadvantaged neighborhoods and have had little opportunity to exit.

Finally, neighborhood racial stratification may predict higher eviction rates due to some form of social control, or racial queuing effect, that coincides with urban revitalization. There is a long history of evictions caused by racial competition for housing and resources fueled by legacies of racial discrimination (Connolly, 2014). For example, one of the major goals within urban revitalization is to implement policy and market driven initiatives to remove blight and problem tenants (Amato and Manuel, 2012). This choice structure on who to remove may be clouded with racialized biases that target non-White tenants over others. Removal could come in the form of anti-crime measures, or a way to send a message to surrounding tenants that certain behaviors and activities are not accepted. While believed to target problem tenants (Braga and Bond, 2008; Buron et al., 2002; Hamilton-Smith, 2002) studies find a temporal association where the increase of these types of removals coincide with gentrification in and around the area (Byrne, 2003).

The introduction of new residents through gentrification also disrupts the social order of neighborhoods and may increase unwanted surveillance for low-income tenants (Barton and Gruner, 2016). Along with increases in eviction, gentrification tends to experience a short upswing in crime (Kreager et al., 2011) resulting in increasing surveillance in already pressured neighborhoods by both formal and informal actors (Guest et al., 2008). Furthermore, gentrifying residents may bring with them competing views on how social control should operate in their new neighborhood. This may increase the likelihood of calls to the police for any social or physical disorder, which in turn could trigger a landlord to remove a tenant who is deemed problematic or simply to avoid the trouble of dealing with the police (Desmond, 2012). Research in Seattle, WA suggests that gentrifying neighborhoods see a higher risk of complaints against Black individuals as compared to other types of neighborhoods, but not a higher likelihood of arrest (Thomas et al., 2016). These types of contacts may result in undue attention from landlords who apply stricter rules to offending tenants.

3.2.3 The Contested Spaces Framework

The third theoretical framework suggests that the geographic concentration of evictions may be affected by housing competition forecasted by nearby housing markets, demand signaled through socioeconomic dynamics, and racial stratification. In the case of developing metropolitan economics, population growth brings increasing competition for spaces where residents seek neighborhoods with preferred features within their price-point (Logan and Molotch, 1987). Potential shifts in nearby areas may provide a forecast for local developers and landlords for possible improvement, motivating them to clear space for potentially higher paying tenants. The influence of extra-local contexts has been tested in prior spatial research which finds nearby neighborhood dynamics having a significant effect on local conditions in terms of residential mobility, crime, and poverty (Crowder and South, 2008; Sampson, 2012; Sharkey and Faber, 2014).

Specific rent, poverty, and racial typology conditions in nearby neighborhoods may have a unique effect on local eviction rates. For example, given that King County is seeing rapid increases in rent, more affordable spaces should be in higher demand. Low poverty neighborhoods, on their own, may be proxy of desirability for the area, making it higher in demand. Affordability coupled with low poverty would make that area even more attractive to households seeking good neighborhoods. Now, if a focal neighborhood has high poverty and low rent, which according to the housing market framework would increase the eviction rate on its own, proximity to low poverty and low rent areas may increase the likelihood of eviction even more as it may signal to local landlords that there is an opportunity to replace low-income tenants with higher-earning ones. However, if a high poverty neighborhood is near another high poverty area, then there is no real benefit to evict low-income tenants as there is not a higher likelihood to replace them with higher-earning households. In short, both nearby poverty and rent should be negatively related with evictions.

Regarding racial composition in nearby areas and evictions, areas that are diverse or have higher Black or Latino representation may be areas that are experiencing gentrifying processes and, therefore, may forecast opportunity to increase rents if areas are improving over time. Consider the example scenario where an economic boom may attract wealthier households to an area and increase the median rent within, and around, a business core. Middle-income residents may then choose to move into historically segregated or diverse areas due to their relative affordability and familiarity. Legacy residents who weathered stagnant wages and neighborhood disadvantage in these destinations are then faced with being priced-out as incoming residents, or nearby gentrification, may inspire landlords to increase local rent. This domino effect across the metro could increase evictions in focal neighborhoods, especially when nearby areas are experiencing similar gentrifying processes in diverse neighborhoods. Therefore, nearby diversity should predict higher rates of eviction in the focal neighborhood. These broader economic and racial conditions are assessed by modeling both local and extra-local measures.

3.2.4 Study Area

The study area of King County, WA fits well within the previously mentioned scenario of economic growth and changing neighborhoods. Within the county are the cities of Seattle, Bellevue, and Redmond; home of tech giants Microsoft, Amazon, and Google as well as high levels of gentrification and increasing rents (Fowler, 2016; Kreager et al., 2011; McGee, 2007). In 2016, King was the 4th largest population-gaining county in the nation with about 460 new migrants per week and an overall population of 2.15 million (US Census Bureau, 2017). King County has a relatively low minority population with 63% White, followed by 15% Asian, 9% Latino, and 6% Black.

These economic and population dynamics provide several benefits for examining the proposed three theoretical frameworks beyond simply improving generalizability through the addition of another study area on evictions. The racial composition of King County provides an opportunity to investigate how racially diverse neighborhoods may relate with evictions. From prior research on Milwaukee, WI, we know that segregated Black neighborhoods had an exceptionally high rate of eviction. However, this finding may have been unique to the citys demographic composition. Contemporary metros with high minority representation have more segregated minority populations across larger spaces (e.g., Detroit, Chicago, and New York), while low minority representation, such as in King County, should exhibit more integration among minority and majority populations (McKinnish et al., 2010). Milwaukee sits within the former category with 36% White, 39% Black, 18% Latino, 4% Asian, and 3% other (U.S. Census Bureau, 2017). The different metropolitan racial compositions should produce distinctive neighborhood racial types between the two areas (e.g., Integrated, White-Asian, White-Black shared), providing an opportunity to test whether racial disparities in evictions persist in Whiter metros. Also, the thriving economy, gentrification, and relatively low poverty in King County provides an opportunity to test how different housing markets and economies relate to evictions given these conditions.

The historical contexts behind King Countys neighborhood formations may inform whether racially diverse neighborhoods are more prone to evictions because they are transitioning spaces, rather than stably integrated. Over the past forty years, Seattles non-White population has been drifting into south King County, either as an opportunity to improve household outcomes (e.g., middle-class Black flight) or by being priced-out of gentrifying areas located near Seattle and Bellevues business districts (McGee, 2007). This results in formerly segregated neighborhoods, both White and non-White, converting into diverse neighborhoods between 1980 and 2010. If incoming gentrifiers increases demand and costs for housing (Formoso et al., 2010; Hwang and Sampson, 2014), then we should see higher rates of eviction in these integrated neighborhoods. Furthermore, if signs of gentrification are occurring in nearby neighborhoods, then we may see extra-local diversity increasing local eviction rates (Byrne, 2003).

3.2.5 Hypotheses

Using these three frameworks, I propose the following hypotheses: Regarding the housing market framework in the focal neighborhood, (H1a) rent should have a negative relationship with evictions as more affordable areas are a scarce commodity in a rapidly growing metro. Due to this scarcity, low income households may contest their eviction by staying beyond their date to leave as there are few neighborhoods they could afford to move to. Likewise, (H1b) local poverty should have a positive relationship with evictions given the higher proportion of low-income households in the area. I also hypothesize that the effect of rent may moderate (change the strength or sign) the effect of poverty. To test this, an interaction term between the two is included in the analysis.

Regarding differences in racial typology of a neighborhood, (H2) local tracts with more diversity or Black or Latino presence should see a positive relationship with evictions net of local rent and poverty. This tests the racial stratification framework, which posits that Black and Latino households tend to face the highest rates of eviction, while at the same time, these areas are transitioning spaces (i.e., becoming more preferable to higher-earning households) and in higher demand due to their affordability and proximity to downtown areas.

Finally, the contested spaces hypothesis suggests that (H3) extra-local market, poverty, and racial compositions will affect local eviction rates where (H3a) nearby rent and poverty will have a negative relationship while (H3b) nearby diverse neighborhoods will have a positive relationship. The negative relationship of nearby rent assumes that affordable spaces are a scarce commodity, especially for King County. Negative poverty suggests that nearby low poverty areas are more preferable spaces and may attract higher earning households, triggering local landlords to consider making space for higher earners in their own neighborhood. Finally, the positive relationship of diversity refers to transitioning spaces that may also forecast demand and potential opportunity for local landlords to gain higher-earning tenants.

3.3 Data

This analysis uses King County, WA court record data used in the previous two chapters (see chapter 2 for more details). Records consist of 5,111 unlawful detainer cases, civil lawsuits filed by landlords to evict tenants, in 2013. Demographic and income data are drawn from the 2010 to 2014 5-year ACS estimates at the tract level. Rent data are drawn from Zillows 2013 tract estimates, a more accurate measure than ACS rent estimates due to Zillows more frequent collection of monthly rent statistics and broader collection strategy. Arguably, tracts are not a perfect definition for neighborhoods as residents tend to operate inside and outside the boundaries of their neighborhood on a daily basis, are not necessarily dedicated to a single place, and have differing definitions of what their neighborhood is over time (Lee et al., 2008). Nonetheless, scholars argue that census tracts come close to the definition of a neighborhood and are sufficient for understanding neighborhood associations (Crowder and Downey, 2010).

The study area of King County provides a unique and useful backdrop for studying evictions. As one of the fastest growing counties in the US, King County has a diverse range of neighborhoods and socio-demographic compositions that captures rapidly changing conditions in a fast-paced economy (Fowler, 2016). In King County, the median household income was $75,302 between 2011 and 2015. For Whites, the median household income was $80k, where 79% of males and 71% of females ages 16 and older were employed. Black households have the lowest median household income below $39k with 65% of males and 61% of females over the age of 16 being employed. Black and Latino households rent at higher rates (57% and 52%) than Whites (30%) making them more vulnerable to evictions. According to yearly reports from the department of Housing and Urban Development, low-income status for a family of four, is between low-income ($64,000) and extremely low-income ($26,000) for the county (Housing and Urban Development, 2013).

3.4 Analytical Strategy

3.4.1 Negative Binomial Modeling Strategy

For this chapter, I use a negative binomial regression on the count of evictions for each tract due to over-dispersion in the count data with a mean of 12.9 and variance of 226.7. Using these data on an OLS model violates several assumptions and, therefore, a negative binomial model (NB) is preferred to help deal with over-dispersion found within the count DV. Prior research on crime counts has popularized the use of negative binomial estimation when examining counts where there is often over-dispersion due to the clustering of events that occur in some areas more frequently than others (Gelman et al., 2007). Research on historical data for lynchings has also found that the use of a negative binomial can be a better model for over-dispersed data as compared to Poisson and modified Poisson regressions (Beck and Tolnay, 1995).

The preference of NB over the familiar ordinary least squares linear model (LM) is due to the failure of several assumptions required by the LM. First, the dependent variable should be continuous whereas count data are discrete. Second, count variables are truncated at zero where the LM prefers non-truncated variables. Third, the LM is best used with a normally, or symmetric, distribution whereas count data have a distinct asymmetry (Beck and Tolnay, 1995).[1] While logging the counts of evictions would alleviate some of these issues, a number of sampling zeros in the eviction count data produces non-number outputs and eliminates 6% of the dataset.

An alternative to the LM approach is to model count data along the Poisson distribution, which analyzes discrete events that are randomly and independently distributed across time or space. However, one of the main properties of the Poisson is that there should be no over-dispersion where the mean should equal the variance. In the presence of over-dispersion, the Poisson distribution will provide misleading associations, leading to underestimated standard errors and optimistic t-ratios (Beck and Tolnay, 1995; Gelman and Hill, 2007). The Quasi-Poisson (or modified Poisson) family of the general linear model can accommodate over-dispersion by shifting the standard errors upwards by assuming the variance is a linear function of the mean and producing a fit that follows along the over-dispersed data. The negative binomial regression follows a similar principle but shifts the standard errors using a quadratic function to better fit the over-dispersed data. Testing model fits of the Poisson, Quasi-Poisson, and negative binomial of the full final model for this study shows a strong preference for the negative binomial over the other two (see Table 3.3 for comparative results of Poisson, Quasi-Poisson, and Negative Binomial).

The dependent variable of the model is the count of evictions, however, a rate of evictions is a preferred interpretation over the raw count for two main reasons. One, renters are the population at risk of eviction and a rate helps determine the risk ratio with different tracts. Two, eviction counts fall within tracts, which is a unit of observation that features varying boundary and population sizes. A rate of the dependent variable accommodates these characteristics providing an outcome that is proportional to these varying dimensions. To interpret these findings as rates, a logged offset of all

[1] Another model that could be used is a zero-inflated negative binomial which separates the data into two categories, zero evictions and non-zero evictions. This approach is best used when there is an excess number of zeros, however, there are only 25 zero counts in the data, which is about 6% of the 397 tracts observed.

renters[2] is included on the right-hand side of the equation. For the negative binomial, this logged offset predictor becomes the denominator exposure (renters) and the count of contested evictions becomes the numerator. The rate for the negative binomial model starts with this structure

$$log(\frac{y}{z}) = \beta' X_n$$

where y is the count of evictions and z is the count of renters for the given tract and $\beta' X_n$ is the respective input. This is then written as

$$log(y) - log(z) = \beta' X_n$$

$$log(y) = \beta' X_n + log(z)$$

where the logged exposure r is now an offset on the right-hand side of the equation. The subsequent coefficients of this model are then interpreted as the exponential rate of evictions per unit exposure (renters) for the given median centered explanatory variable.

3.4.2 Spatial Cross-Regressive Modeling

While local effects can be directly measured using traditional inputs, the extra-local effects require a spatial strategy that accounts for proximity and weighted measures of the nearby values. To

[2] Arguably, not all renters are at risk of eviction and, therefore, a denominator of renters at risk could be used in lieu of all renters (e.g., renters that contribute 30% to 50% of their income to rent). However, for this study, I choose all renters for these reasons: First, my main intention for this analysis is to evaluate the overall ecological understanding of evictions, like an overall rate of mortality in a country, where using all renters achieves this goal. Decomposing renters by rent burden starts to delve into individual level assumptions using aggregate level data (i.e., ecological fallacy) and requires different questions about the population, which strays from a broader ecological framing of this work. Second, analysis using renters with 30% and 50% rent burden did not significantly change the findings. There was a slight increase in the overall eviction rate, however, using a 30% cutoff is exceptionally conservative given that past research shows evicted tenants contribute upwards of 80%-90% of their income to rent. The 50% cutoff also introduced strange outcomes through multicollinearity. Third, not all evictions are due to rent burden, where some households may have the means to pay but simply do not for some reason. To start analyzing different types of renters would require individual level data that is not available at this time.

create these extra-local measures, I utilize a spatial cross-regressive model, which is similar to, but simpler than, a spatial autoregression model. Traditional spatial autoregression models require a spatially lagged measure of the outcome variable as a predictor to understand to what extent the dependent variable is affected by lagged values of the dependent variable. However, given the hypothetical focus on the local and extra-local market, economic, and racial composition on the local eviction rate, spatially lagged versions of the key independent variables are produced. This technique is closely modeled after a study by Crowder and South 2008 on the local and extra-local neighborhood dynamics of White out-migration from neighborhoods of origin. The benefit of using lagged independent variables in this manner allows the model to specify separate effects of local and extra-local conditions on the focal tracts eviction rate while maintaining the structure, interpretation, and avoiding violation of generalized linear model assumptions of the negative binomial regression.

The cross-regressive model follows closely to the linear regression

$$y = X\beta + WX\gamma + \epsilon$$

with the familiar y dependent variable observation, X as the explanatory variable, and β regression coefficient vector. The spatial weights matrix of the lagged independent variables is captured by the $WX\gamma$ operator where the W is the spatial weights matrix based on the total number of tracts in the state summarizing the relationship of each tract (row) to all other tracts (columns) in the matrix. The γ is the extra-local tract value multiplied by the WX spatial lag operator, matching the column dimensions of WX. From there, the extra-local variable X is summed across all the weighted distances for the respective tract $i(\sum_j w_{ij} X_j)$. In simpler terms, the $WX\gamma$ spatial lag operator can be interpreted as the weighted average of values on the explanatory variable of interest (e.g., the weighted average of nearby median rent). The spatial lag variable is treated as a separate contextual variable to determine possible additive effects on the dependent variable.

The spatial dependence of extra-local tracts decays with distance. Therefore, a spatial weighting strategy that accounts for the varying influence of nearby tracts is employed using an inverse weighted distance (IDW) squared scheme for each tract that falls within a maximum distance of 16 kilometers (9.94 miles, which is about .75 times the maximum distance between all tracts in King County).[3] Under this strategy, the IDW squared spatial weights matrix is defined as $w_j = 1/d_{ij}^2$ where d_{ij}^2 is the geographic distance between the centroid of tract i and the centroid of the extra-local tract j. Any tract that falls outside of the 16-kilometer threshold has a weighted value of 0.

The distance-decay strategy allows immediately neighboring tracts to have the greater influence on local evictions. The distance-decay function also helps evaluate the contested spaces theory more efficiently above an adjacency strategy where the influence of the housing market, economics, and racial compositions just beyond the immediate neighbors is accounted. The distance decay strategy is applied to all tracts within Washington State, where I then select tracts only within King County for the analysis. This method allows tracts bordering King County to pick up extra-local effects that fall outside of the boundary of the county. Restricting the distance-decay effects only within King County would omit important rural and urban areas that fall just outside the county boundary and produce misleading assumptions.

3.4.3 Dependent and Independent Variables

This key dependent variables is the overall count of evictions interpreted as a rate using a logged offset predictor of all renters (total evictions / total renters) within each of the 397 King County census tracts. The primary independent variables are the centered local and extra local neigh-

[3]A Morans I and Gearys C coefficient correlogram was calculated for the neighborhood weights matrix to find the most efficient distance according to the spatial distribution of eviction rates in King County. Other distances were considered, however, in the end the threshold of 16 km was the greatest distance with the most significant p-value (see Bivand, Pebesma, and Gmez-Rubio 2013 for further discussion).

borhood characteristics of race, poverty, and rent. To address the first hypothesis on the housing market, I use Zillows estimated median rent data for 2013 and 2010 to 2014 ACS 5-year estimate defined poverty at the tract-level. Each variable is centered to the median value of the county. Racial composition of the neighborhood is defined as a six-category racial typology of King Countys neighborhoods: White-shared, White-Asian, White-Latino, White-Black, White-mixed, and integrated. The majority of King County tracts are dominated by White residents, with varying levels of other groups. The White-mixed and integrated neighborhoods represent diversity in the tract. The former category is mostly White, but has multiple high, non-White groups represented in the tract. These categorical variables take a value of 1 if the tract is of the respective type of neighborhood and a 0 if not. To test the contested spaces theory, I use the centered extra-local neighborhood characteristics of rent, poverty, and neighborhood racial typology to determine the effects of nearby dynamics. These extra-local values are interpreted as the weighted average value of rent and poverty in nearby tracts while the categorical variable of racial typology is interpreted as the average likelihood that the a nearby tract is of a given racial typology.

3.5 Results

3.5.1 Descriptive Statistics

Table 3.1 provides the means and standard deviations for the King County racial and renting population and model variables. The racial composition of King County is mostly White (64%) followed by Asian (15%), Latino (9%) and Black (6%). Among each of these racial groups, the percent of renters is reversed in order with Black households renting at 72%, Latino at 66%, Asian at 43%, and White at 37%. In 2013, King County had an overall eviction rate of 1.5% with Black households facing the highest rate of 4.6%; about 3.7 times higher than Whites ($.046/.013 = 3.7$). Asian and Latino households saw a much lower ratio compared to Whites of 0.5 and 1.6.

King County has a relatively high average median income of $78,000, ranking within the top

4% of the nations county median incomes (U.S. Census Bureau, 2017), and an average tract-level median rent of nearly \$2,000 across all bedroom types; ranking within the top 50 counties in rent for the US (Zillow, 2017). Asian households have the highest tract-level average median income (\$85k), followed closely by Whites (\$82k), then Latinos (\$68k), and Black households (\$49k). The ratio of average tract median rent to income for Black households is roughly 47% $(1922/49246 = 0.468)$.

King Countys neighborhood racial make-up consists mostly of White-Asian, White-shared (relatively mostly White), and White-mixed (relatively diverse). The highest rates of eviction fall mostly within the most diverse neighborhoods of White-Latino, integrated, and White-mixed (2.7% to 2.1%). The extra-local racial compositions indicate that tracts surrounding local areas were mostly White-Asian, followed by White-shared, and White-mixed neighborhoods with a spatially-weighted average of 35%, 24%, and 22%, respectively. Nearby median rent was \$1,880 while nearby extra-local median income is on average \$75,796 with a standard deviation of \$18,302.

Figure 3.1 shows the geographic distribution of unlawful detainers, neighborhood racial typologies, median rent, and rent burden. By and large, 57.6% of evictions occurred in South King County, where most of the diverse neighborhoods, lowest rent, and highest rent burden is located. Conversely, lower rent burdened areas and higher rent is centrally located within Seattles city limits, with 26% of the countys evictions, and the easterly city of Bellevue with 15.2% of the countys evictions.

3.5.2 Overall Eviction Rate Model

Table 3.2 presents the results for four negative binomial models for local housing market, racial neighborhood typology, and extra-local effects on the tract level eviction rate. Model 1 tests the housing market hypothesis by examining the local median rent and poverty. Overall, this model supports the hypothesis with a negative relationship with rent and positive, but non-significant, relationship for poverty. The intercept provides the base eviction rate of $e^{-4.21} = 0.015$ where a \$1,000 increase in the centered rent variable has a negative multiplicative effect of $e^{-1.05} = 0.35$, or a 65% reduction in, the eviction rate. Poverty is positive but non-significant. Model 2 introduces the interaction of rent and poverty with a strong negative multiplicative effect of $e^{-5.14} = 0.005$, meaning that a 100-percentage point change in poverty leads to about a 99% decreasing difference in rent. This is a large coefficient that ultimately loses significance in Model 5 once extra-local effects are controlled.

Model 3 includes the local racial typology of the neighborhood where, as compared to mostly White neighborhoods, White-Latino, White-mixed, and integrated neighborhoods have a significant positive multiplicative effect of 2.15, 1.57, and 1.84 on the eviction rate net of rent and poverty. The coefficient of rent decreases slightly, but now poverty is significant and negative, which is opposite of the hypothesis. However, Model 4's inclusion of extra-local effects of nearby rent, poverty, and racial typology changes the local poverty sign to positive while local rent and the interaction loses significance. In addition, integrated neighborhoods lose significance while White-Black neighborhoods gains significance, with all effects being positive.

What is most interesting about Model 4 is the supremacy of extra-local effects. Nearby poverty has a strong 0.005 multiplicative decreasing effect on the eviction rate meaning that focal areas near low poverty neighborhoods have a much greater likelihood of a high eviction rate. Likewise, extra-local rent is negative and significant, but still not as strong as nearby poverty. Finally, nearby racial typologies, except for White-Black, are significant and have a positive coefficient. This means that living near a neighborhood with higher minority populations or overall diversity increases the likelihood of eviction in the focal area. These findings give good evidence to the contested spaces theory suggesting that nearby low-poverty neighborhoods, along with affordability, increases the likelihood of eviction especially when tracts are near diverse or higher minority represented neighborhoods.

3.5.3 Predicted Plots

To help visualize these trends in Model 4, Figure 3.2 and Figure 3.3 highlight the effects of local and extra local poverty for the six different local racial typologies. Figure 3.3 is the local poverty confined to the 5% and 95% quantiles. Net of all other variables, including extra-local effects, we see the overall positive relationship with the eviction rate where White-Black neighborhoods have the highest rate across the x-axis. White-Latino and White-mixed are the other two significant effects and fall below the White-Black typology. Overall, living in a neighborhood that has over 10% black representation in experiences eviction rates ranging from about 1.3% in lower poverty areas to about 1.9% in higher poverty areas. White-Latino see about 1.2% to 1.6% increase and White-mixed see about a 1% to 1.3% increase. White-shared neighborhoods (i.e., mostly White) have the lowest eviction rate of all groups with rates falling about 0.5% points below the White-Black neighborhoods.

Figure 3.3 highlights the negative relationship of nearby poverty on local racial typologies. Again, we see the same order where White-Black neighborhoods have the highest rates and White-shared have the lowest. Low-poverty neighborhoods (left-side) have a greater gap than higher poverty neighborhoods (right-side), which highlights the large coefficient of -5.21 in Table 3.2, Model 4 and suggests that as nearby poverty increases, the local racial typology of neighborhood matters slightly less (i.e., the gap is smaller between White-Black and White-shared). For White-Black neighborhoods, nearby high-poverty has about a 2.2% eviction rate falling to about a 0.9% eviction rate near high-poverty areas. White-shared ranges from about 1.3% on the left to above 0.5% on the right. These trends suggest a protective factor about living in mostly White neighborhoods while White-Black households are at the greatest risk of eviction. In part, the negative relationship with nearby low-poverty reinforces the hypothesis that there is some type of preferable feature about low-poverty neighborhoods that may attract higher-earners and possibly trigger more evictions in the focal area. Individual-level data on households and landlords would help disentangle this effect.

3.6 Conclusion

While most literature on residential mobility identifies reasons why households choose to move, emerging research on evictions examines the reasons and consequences of forced mobility among low-income households (Desmond et al., 2015). This field of study has, thus far, focused mostly on household level conditions leading to eviction, such as the structural constraints of stagnant wages, rising housing costs, and inadequate welfare (Desmond, 2012). Among the evicted, Black, Latino, and female-headed households face the brunt of evictions. However, little is known about the ecological dynamics of evictions. A few studies have identified high rates of eviction occurring in Black and mixed-race neighborhoods with high rates among Black and Latino households, even within mostly White neighborhoods. While housing and economic associations of gentrification are possible predictors of forced mobility (Aratani et al., 2011; Desmond, 2012; Hwang and Sampson, 2014), there is conflicting evidence whether there is a direct relationship with gentrification (Desmond and Gershenson, 2017) requiring a more in depth analysis of neighborhood dynamics that may be at play.

This study adds to the existing research on evictions by evaluating the local and extra-local neighborhood dynamics associated with geographic concentrations of evictions. Using a novel dataset of unlawful detainer court records, Zillow rent data, and US Census data for King County, WA, I examine the spatial influence of local and extra-local neighborhood racial compositions, poverty, and housing markets. Drawing from research on evictions, residential mobility, and segregation, I test the hypotheses that local poverty, diversity, and minority presence in the neighborhood is positively associated with evictions; rent is negatively associated; nearby poverty and rent is negatively associated with evictions; and nearby diverse and White-minority shared neighborhoods are positively related. Results show support for all hypotheses.

Main findings show that neighborhood racial composition and poverty play primary roles within the focal area. However, extra-local effects of poverty, rent, and racial typology have the strongest effects overall on predicting eviction rates. Under these conditions, living in a high poverty neighborhood and nearby a low poverty and affordable tract has the highest effect on evictions, which only increases the closer the focal tract is to a diverse or White-Black tract. Overall, rent does not seem to matter as much as the racial composition and poverty.

The role of diversity and poverty in both the focal and extra-local contexts increasing eviction rates in the focal area suggest that nearby neighborhood conditions provide a forecast for local landlords on whether they could replace low-income tenants with higher-earning ones. Over the past 40 years, King Countys contemporary diverse neighborhoods were once either highly segregated minority or White. With recent economic increases in the heart of Seattle and Bellevue, middle-earning households have sought cheaper housing in areas near business corridors or in the suburbs, spurring population growth in formerly disadvantaged tracts. Also, the high rates of eviction within, and nearby, diverse neighborhoods suggest that these areas are risky for low-income households as they are more likely to be changing spaces.

Overall, this analysis suggests that spatial contexts play an important role in the process of evictions, especially when accounting for nearby effects. However, there are several limitations to the analysis. For one, individual-level dynamics would greatly improve our understanding of the extent to which the housing market and socio-economics plays in this analysis. The most common question coming out of this analysis is to what extent do landlord decisions play in who gets evicted, and where? Also, individual-level economics would help us better understand mechanisms of poverty in these neighborhood contexts. For example, what are the characteristics of those that get evicted in Whiter neighborhoods? Finally, this analysis may raise more questions than it answers in terms of neighborhood contexts. Specifically, how do changes in a neighborhood relate to these effects? More specifically, how does increasing demand and population growth relate to current eviction rates? This exact question leads to my analysis of Chapter 4.

Table 3.1: Descriptive Statistics for the King County Population

	King County	Asian	Black	Latino	White
	Individual & Renting Population				
Individual Count	2,008,997	304,838	120,457	184,318	1,275,468
% of population		15%	6%	9%	64%
Renting households	344,104	44,234	34,330	35,060	211,357
% of renting pop		43%	72%	66%	37%
	Evictions				
% of evicted renters	1.5%	0.6%	4.6%	1.6%	1.3%
Avg. tract ev. rate	1.6%	1%	3.6%	1.8%	1.5%
(SD)	(1.6%)	(2.9%)	(5.1%)	(3.4%)	(1.7%)
Rate ratio to Whites		0.51	3.71	1.3	—
	Economics & Housing Market				
Avg. tract med. income	$78,606	$84,574	$49,246	$67,660	$82,293
(SD)	($30,825)	($41,060)	($32,280)	($41,622)	($30,334)
Avg. Median Rent	$1,922				
(SD)	($524)				
Avg. rent burden	45%				
(SD)	(13%)				
Avg. nearby med. rent	$1,880				
(SD)	($332)				
Avg. nearby rent burden	45%				
(SD)	(7%)				

	Neighborhood Racial Typology					
	Integrated	White Asian	White Black	White Latino	White Mixed	White shared
Count	41	134	9	19	87	107
Eviction rate	2.6%	1.2%	1.4%	2.7%	2.1%	1.1%
(SD)	(1.8%)	(1.6%)	(1.3%)	(1.7%)	(1.3%)	(1.3%)
Extra-local likelihood of neighborhood type	0.12	0.35	0.02	0.05	0.22	0.24
(SD)	(0.15)	(0.22)	(0.04)	(0.08)	(0.15)	(0.21)

Data source: ACS 2010-2014, Zillow tract-level rent data, & King County Courthouse Unlawful Detainer Cases for 2013

Table 3.2: Negative Binomial Regression Analysis for the Overall Rate of Unlawful Detainers in 2013

	Model 1	Model 2	Model 3	Model 4
(Intercept)	$-4.21\ (0.04)^{***}$	$-4.26\ (0.04)^{***}$	$-4.51\ (0.08)^{***}$	$-4.72\ (0.08)^{***}$
Poverty	$0.13\ (0.44)$	$-0.67\ (0.47)$	$-1.17\ (0.48)^{*}$	$0.97\ (0.48)^{*}$
Rent	$-1.05\ (0.11)^{***}$	$-1.07\ (0.11)^{***}$	$-0.77\ (0.12)^{***}$	$-0.06\ (0.12)$
Rent * Poverty		$-5.14\ (1.32)^{***}$	$-3.56\ (1.33)^{**}$	$0.50\ (1.18)$
Mostly White			$---$	$---$
White-Asian			$0.08\ (0.10)$	$0.03\ (0.11)$
White-Latino			$0.77\ (0.16)^{***}$	$0.38\ (0.14)^{**}$
White-Black			$0.31\ (0.29)$	$0.49\ (0.24)^{*}$
White-Mixed			$0.45\ (0.11)^{***}$	$0.20\ (0.11)^{\dagger}$
Integrated			$0.61\ (0.15)^{***}$	$0.20\ (0.15)$
Extra-Local Poverty				$-5.21\ (1.17)^{***}$
Extra-Local Rent				$-0.76\ (0.16)^{***}$
Extra-Local White-Asian				$0.61\ (0.27)^{*}$
Extra-Local White-Latino				$2.40\ (0.41)^{***}$
Extra-Local White-Black				$-1.75\ (1.33)$
Extra-Local White-Mixed				$1.93\ (0.27)^{***}$
Extra-Local Integrated				$1.30\ (0.37)^{***}$
AIC	2526.28	2512.15	2490.48	2360.79
BIC	2542.22	2532.07	2530.32	2428.52
Log Likelihood	-1259.14	-1251.07	-1235.24	-1163.40
Deviance	443.92	438.24	440.79	441.83
Num. obs.	397	397	397	397

$^{***}p < .001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Data source: ACS 2011-2015, Zillow tract-level rent data, & King County Courthouse Unlawful Detainer Cases for 2013

Table 3.3: Comparison of Poisson, Quasi-Poisson, and Negative Binomial Models

	Poisson	Quasi-Poisson	Negative Binomial
(Intercept)	$-4.79\ (0.05)^{***}$	$-4.79\ (0.10)^{***}$	$-4.72\ (0.08)^{***}$
Poverty	$1.03\ (0.23)^{***}$	$1.03\ (0.47)^{*}$	$0.97\ (0.48)^{*}$
Rent	$-0.02\ (0.07)$	$-0.02\ (0.15)$	$-0.06\ (0.12)$
Rent * Poverty	$1.18\ (0.58)^{*}$	$1.18\ (1.19)$	$0.50\ (1.18)$
Mostly White	$---$	$---$	$---$
White-Asian	$0.13\ (0.06)^{*}$	$0.13\ (0.13)$	$0.03\ (0.11)$
White-Latino	$0.44\ (0.07)^{***}$	$0.44\ (0.15)^{**}$	$0.38\ (0.14)^{**}$
White-Black	$0.55\ (0.13)^{***}$	$0.55\ (0.27)^{*}$	$0.49\ (0.24)^{*}$
White-Mixed	$0.27\ (0.06)^{***}$	$0.27\ (0.13)^{*}$	$0.20\ (0.11)^{\dagger}$
Integrated	$0.24\ (0.07)^{**}$	$0.24\ (0.15)$	$0.20\ (0.15)$
Extra-Local Poverty	$-4.40\ (0.59)^{***}$	$-4.40\ (1.21)^{***}$	$-5.21\ (1.17)^{***}$
Extra-Local Rent	$-0.85\ (0.09)^{***}$	$-0.85\ (0.17)^{***}$	$-0.76\ (0.16)^{***}$
Extra-Local White-Asian	$0.71\ (0.15)^{***}$	$0.71\ (0.31)^{*}$	$0.61\ (0.27)^{*}$
Extra-Local White-Latino	$2.37\ (0.20)^{***}$	$2.37\ (0.41)^{***}$	$2.40\ (0.41)^{***}$
Extra-Local White-Black	$-2.47\ (0.80)^{**}$	$-2.47\ (1.62)$	$-1.75\ (1.33)$
Extra-Local White-Mixed	$1.76\ (0.13)^{***}$	$1.76\ (0.27)^{***}$	$1.93\ (0.27)^{***}$
Extra-Local Integrated	$1.44\ (0.18)^{***}$	$1.44\ (0.36)^{***}$	$1.30\ (0.37)^{***}$
AIC	2886.16		2360.79
BIC	2949.90		2428.52
Log Likelihood	-1427.08		-1163.40
Deviance	1386.24	1386.24	441.83
Num. obs.	397	397	397

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Standard errors are in parentheses. The Poisson, Quasi-Poisson, and negative binomial lead to somewhat similar results with variation in the p-values. However, the AIC, BIC, and deviance all point to the negative binomial as the better fitting model. Also, a log-likelihood test between the Poisson and the negative binomial are statistically significant by conventional means.

Figure 3.1: Geographic Distribution of Unlawful Detainers, Neighborhood Racial Typology, Poverty, & Median Rent

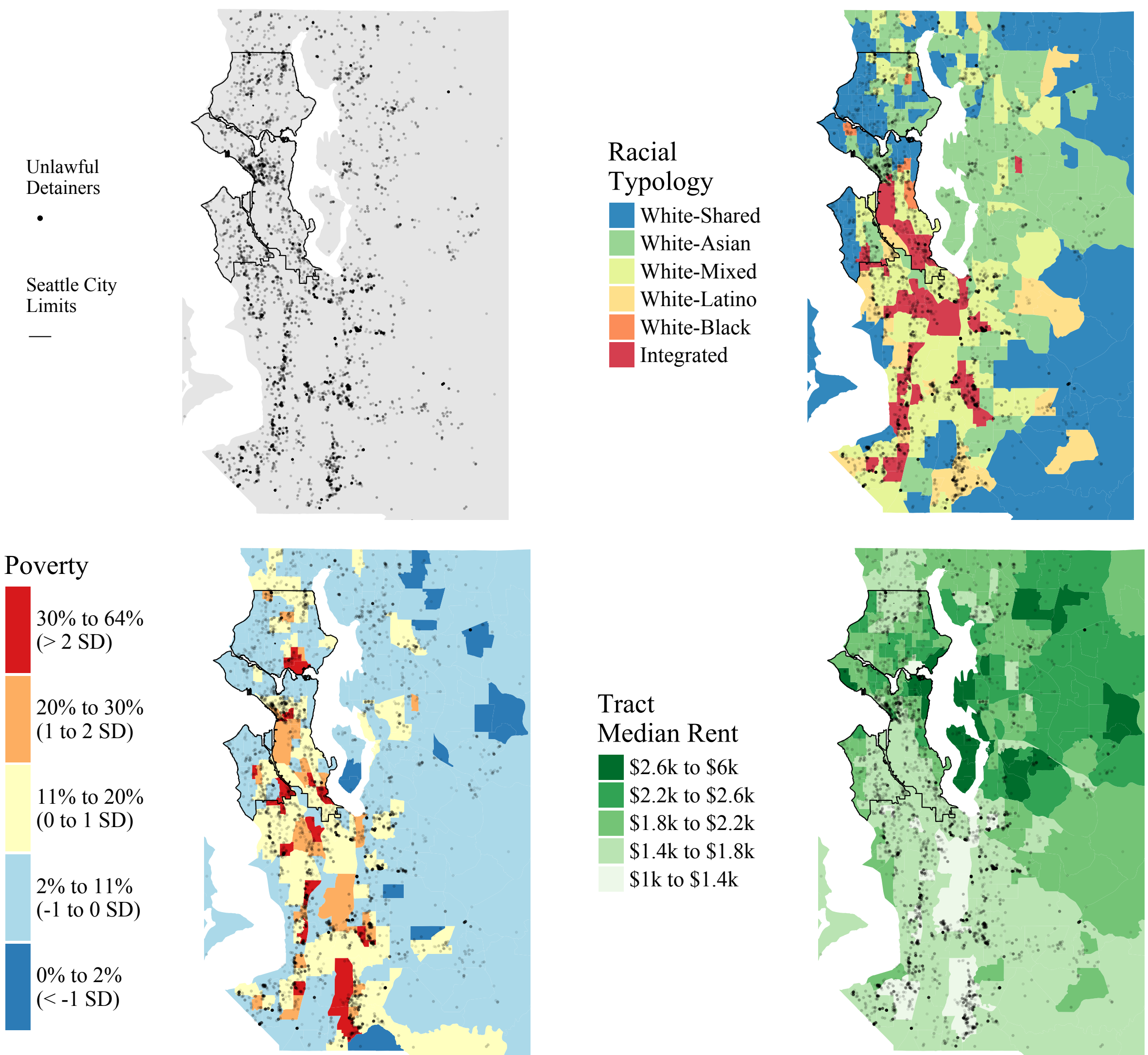
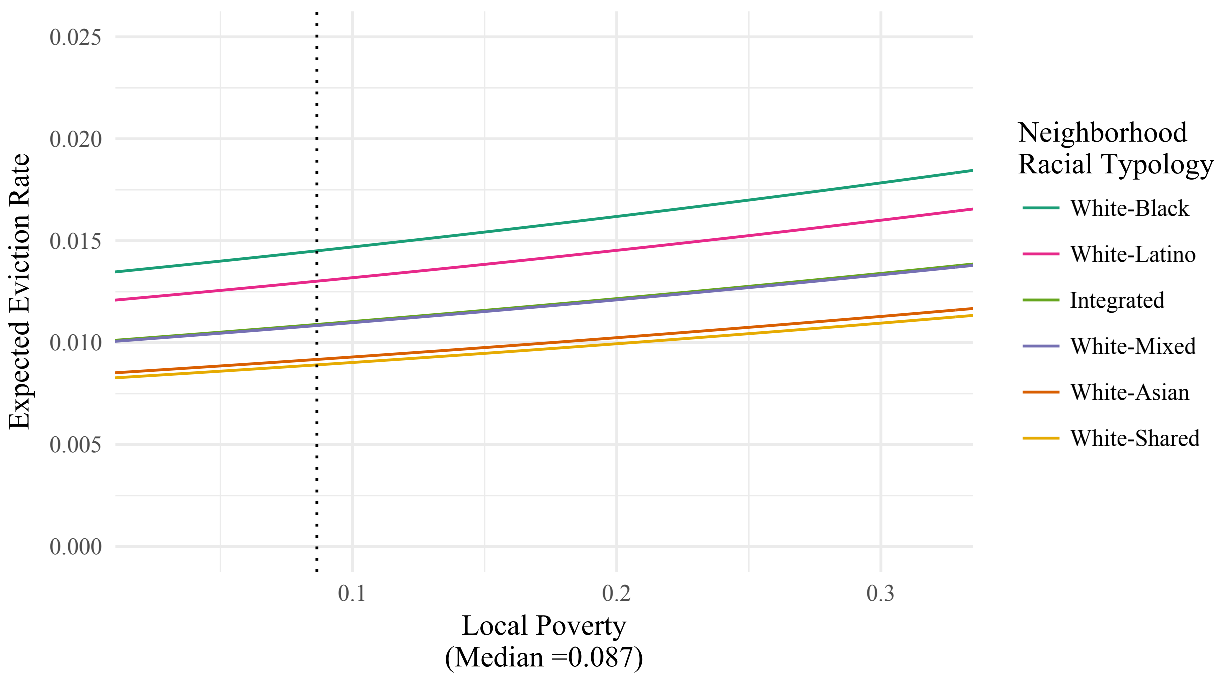
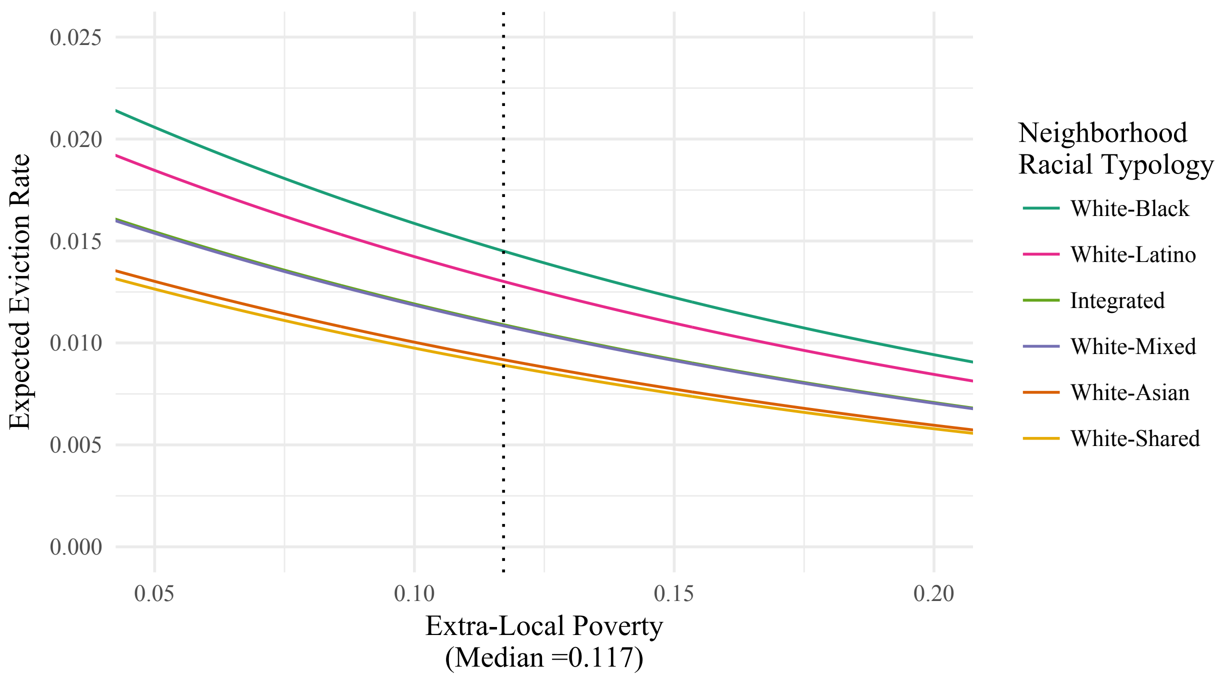


Figure 3.2: Expected Eviction Rate for Local Poverty by Local Neighborhood Typology



Poverty values have been converted from centered to actual values. The dotted line references the median poverty value of 0.087. The x-axis is confined to the inner 5% and 95% quantiles of local poverty.

Figure 3.3: Expected Eviction Rate for Extra-Local Poverty by Local Neighborhood Typology



Poverty values have been converted from centered to actual values. The dotted line references the extra-local median poverty value of 0.117. The x-axis is confined to the inner 5% and 95% quantiles of extra-local poverty.

Chapter 4

NEIGHBORHOOD CHANGE & EVICTIONS

4.1 Introduction

While residential mobility research has focused mostly on a households ability to access better neighborhoods based on available resources, issues of discrimination, and preferences, evictions research aims to understand the mechanisms related to the forced mobility (Desmond, 2012; Krysan et al., 2015). For low-income families, the threat of eviction increases with economic housing burden failing to meet annually increasing rents. Most of the body of research in this area has focused on household-level mechanisms that lead to removal, however, few have tackled the associated neighborhood dynamics related to external pressures. More specifically, how do past market, socioeconomic, and population changes in a neighborhood relate to the contemporary concentration of evictions?

Historically, neighborhood change dynamics have been central to urban sociology research and provide valuable insight into the effects of eviction. From the early investigations of ecological processes of succession and domination of actors optimizing the market in different neighborhoods, to the disparate impacts of segregation and residential mobility, neighborhood changes are a key feature of a citys growth and economics that benefit some while excluding others (Burgess, 1925; Logan and Molotch, 1987; Massey and Denton, 1993). Within the context of evictions, rent inflation through population growth is a common threat to low-income households where household economic precarity increases when, for example, a previously segregated and poor neighborhood becomes an ideal destination for higher-earning households. Unplanned mobility escalates disadvantage for low-income families due to cost of moving, detachment of networks, and high probability of moving to worse neighborhoods (Desmond et al., 2015; Desmond and Perkins, 2016). Investigating these neighborhood dynamics related to forced removal of households is important for understanding how broader metropolitan processes pressure low-income households into deeper disadvantage.

For the few studies that have taken neighborhood characteristics into account, we see that most evictions occur in disadvantaged, Black, and mixed-minority neighborhoods (Desmond and Gershenson, 2017). However, little is known about the demographic shifts that took place leading up to different rates of eviction. Do evictions occur more in neighborhoods that see more improvement or decline as compared to the median change for the county? To what extent does the changing housing market relate to eviction concentrations? And, are socioeconomic or racial changes more important than simple shifts in the housing market?

This chapter expands the assessment of neighborhood dynamics on evictions by investigating different types of tract level demographic and market changes preceding observed eviction rates in King County, WA. Using unlawful detainer court data from 2013 combined with US Census demographic and Zillow rent data, I address several key questions: (1) How do increases in neighborhood socioeconomic status and rent relate to current eviction rates? (2) And, how do eviction rates relate to different racial group and new mover population growth? Results show that evictions are lower in areas with increasing SES, housing, and rent but higher in tracts that saw increases in Black and Latino populations.

4.2 Theory

Three key structural constraints associated with evictions consist of rising housing costs, stagnant wages, and inadequate welfare (Desmond, 2012), which can be divided into household-level effects (low wages and limited welfare support) and neighborhood-level effects (rising housing costs). At the household-level, rent burden plays a primary role in preventing families from maintaining housing stability (Zuk et al., 2015). Women, especially Black women, are more likely to be evicted than men and have the highest household costs, where the probability of eviction increases with the higher number of children in the home (Desmond, 2012; Desmond et al., 2013). Low-income households working at, or near, minimum wage contribute upwards of 80% to 90% of their income to rent resulting in the leading cause of eviction: falling behind on rent. (Desmond et al., 2015). One reason behind this high contribution is that annual increases in rent are outpacing minimum wage and welfare stipends that remain stagnant over decades. Even in high-poverty neighborhoods, where the majority of evictions occur, yearly increases in rent are approaching the total income of welfare recipients (Desmond, 2012).

One understudied topic is the association of neighborhood changes and its effect on increasing housing costs for low-income households. More specifically, the concentration of evictions may have a unique correlation with specific types of demographic changes in socioeconomic status and racial compositions coinciding with subsequent changes in rent, housing supply, and demand. At its core, housing demand increases with population growth where an increasing population size may drive rents higher in an area depending on the available housing supply and the characteristics of the residents (Glaeser et al., 2006). Demand in an area may come in several forms, either in terms of high-income householders looking to move to high-end, preferred neighborhoods (e.g., close to work, walkability, good schools, and other relatable choice structures) driving up rents and pricing out low-income households or through middle-income to low-income households, who may have been priced out of other areas, are looking to find similar characteristics at a price point they can afford. In many cases, the latter group ends up moving to traditionally disadvantaged neighborhoods and changing the housing market value. In both circumstances, housing market agents (e.g., landlords and developers) respond to increased demand and maximize potential profits by clearing space for higher paying tenants and/or increasing housing supply at a rate that would maximize profit (Aratani et al., 2011; Formoso et al., 2010; Maly, 2005).

The exceptionally large population growth and subsequent increases in housing costs in King County (McGee, 2007) have made affordable spaces a scarce commodity. If low-income households are relegated to the lowest rent areas, these spaces may see high rates of eviction as demand for affordable spaces may be higher in King than other counties. In 2000, the median gross rent for all bedroom types was $1,087 (see Table 4.1) and increased to $1,805 in 2013, about a 66% increase over 15 years. Using the 2013 median rent, a household would have to make over $72,000 a year to avoid being rent-burdened (contributing more than 30% of their income to rent). HUDs definition of low income for a family of four is about $64,000, which puts the median rent of $1,805 at about 33% of that households income. The extremely low-income threshold in King is $24,000, which would equate to about 90% of the households income if they were able to find a rental for $1,805. This, of course, does not account for other formal and informal types of income assistance, however, it paints a picture of what constraints low-income households may face. Regardless, a 66% rise in the median gross rent is a sharp increase that applies housing pressure across all income brackets.

One style of neighborhood change that has been examined in relationship to evictions is gentrification, which is characterized by residential displacement of low-income households through revitalization policies and development, the increase of middle-class movers in traditionally disadvantaged neighborhoods, and the decline or removal of affordable housing (Dwyer and Phillips Lassus, 2015; Shaw, 2004). However, the connection between gentrification and the displacement of low-income tenants through eviction is still inconclusive (Desmond and Gershenson, 2017). Gentrifications positive and negative effects have been highly contested due to its difficulty to measure, and, the low-frequency of neighborhoods that fit the definition. On the one hand, while it may increase property value, gentrification also provides greater access to loans, local economic improvement, and integrates traditionally disparate classes and racial groups (Freeman, 2005; Lees et al., 2007). On the other hand, increases in rent still threaten to displace lower-income households when incomes are unable to match the increasing cost of the area (Wyly and Hammel, 2004). Measurement complications arise as gentrification is a micro-level process that is spotty at best with much disagreement regarding its severity (Kreager et al., 2011; Lees et al., 2007; Newman and Wyly, 2006). Gentrification is a multi-decade event (Lees et al., 2007; Wyly and Hammel, 1999) that requires a complex mixed-methods approach using census and ground level observations to produce nominal identifiers on whether an area is gentrifying or not (Hwang, 2015; Kreager et al., 2011; Wyly and Hammel, 2004). Many of these measures are outdated and still produce conflicting evidence about who benefits and who is displaced (Desmond, 2012; Freeman and Braconi, 2004). These complications require researchers to further unpack the gentrification relationship with evictions by including aspects of neighborhood change in non-gentrifying communities (Desmond and Gershenson, 2017).

While there is limited empirical analysis on the connection of neighborhood change and evictions, a basic theoretical framework can still be drawn from what we already know about neighborhood correlates. For example, evidence suggests that evictions occur mostly in neighborhoods that are economically disadvantaged and largely minority (Desmond, 2012). Higher rates of crime and eviction increase the likelihood of eviction, hypothetically due to some locally calibrated style of property management exhibited by landlords responding to local conditions (Desmond and Gershenson, 2017). The preceding chapters also highlight evictions occurring in neighborhoods that are integrated, higher minority, high rent-burdened, further away from business and downtown centers, and in areas with the lowest median rentall conditions that may not have been stable through time. Residential mobility research highlights household efforts to move to neighborhoods that match their racial or socioeconomic preferences while simultaneously changing the demographic composition of a neighborhood (Krysan et al., 2015). These population shifts affect both the destination and origin neighborhood, which leads to potential improvement or decline of a neighborhood. For example, in cases where middle-class households move out of disadvantaged or declining neighborhoods, they leave behind neighborhoods that may increase in poverty (Quillian, 1999). Likewise, their destinations may shift in a way that affect the likelihood of eviction either in a positive or negative way, such as through increasing costs based on population growth or opportunity for landlords to obtain more rent from higher-earning tenants. Examining these mechanisms of change that pressure low-income households into housing insecurity will help both researchers and policy makers understand what trends are more or less beneficial for the most vulnerable.

4.3 Hypotheses

Before moving forward to the hypotheses, a few clarifications are required. First, while the theoretical framework just presented focuses largely on individual level dynamics that may explain neighborhood level associations with evictions, it is important to note that this is an ecological evaluation and not a household-level analysis. Often, it is easy to slip into an ecological fallacy by drawing household level inference from aggregate level results. Therefore, it is important maintain this distinction of ecological dynamics from here on. Second, the structure of the analysis examines the neighborhood changes leading up to 2013 eviction records. Based on eviction theory, one may assume that increasing neighborhood SES would increase the likelihood of eviction. To answer this question, we would require longitudinal eviction data, which is not available at this time. Therefore, the following results focus strictly on neighborhood changes that are associated with contemporary eviction rates (i.e., as of 2013).

With this in mind, the following hypotheses focus on three main neighborhood level effects related to evictionspreceding changes in neighborhood socioeconomic status, the housing market, and racial composition.

1. *Change in socioeconomic status will be negatively related to eviction rates.* This is based largely on prior research that finds evictions occurring most in high poverty and high disadvantaged areas (Desmond, 2012). Change in SES is operationalized using change in educa-

tion and poverty, where higher education and lower poverty would reflect higher SES. Areas that see the lowest levels of improvement in these two characteristics, as compared to the rest of the county, should have the highest rates of eviction.

2. *Change in rent will have a negative relationship with evictions.* Based on the theory that low-rent tracts are scarce in King County, neighborhoods that experienced slower increases in rent (i.e., the most affordable tracts in the county) should have the highest rates of eviction as these spaces are in high demand.

3. *Both rent and SES will have a negative conditional relationship (interaction) with each other.* This assumes that increases in SES coincide with increases in rent to follow demand. Therefore, the effect of changes in rent should be conditional on changes in SES.

4. *Population growth will have a positive relationship with evictions.* General population growth in a tract is a good predictor of demand, regardless of whether they are high-earning or low-earning households, where space becomes limited and evictions should increase.

5. *The proportion of new movers will have a negative relationship with evictions.* Population growth, alone, consists of births, deaths, and migration. However, growth through new mover migration should signal a kind of targeted demand for the area (i.e., there is some intrinsic feature about the area that attracts new movers from either within the county or out of county). Demand of this kind should mean that more economic resources are necessary to access these spaces due to its popularity, and therefore, may be less accessible for low-income households. Therefore, evictions should be lower in the area.

6. *Finally, increases in the Black and Latino population should see a positive relationship with evictions.* This is based on prior findings that Black and Latino households are the most

represented among the evicted in previous studies (Desmond, 2012). Also, research in earlier chapters highlights racial disparities in evictions both at the household level and at the neighborhood level where there are more observed evictions in diverse and Black or Latino neighborhoods.

4.4 Data & Methods

This analysis uses King County, WA court record data used in the previous two chapters (see chapters 2 and 3 for more details). Records consist of 5,111 unlawful detainer cases, civil lawsuits filed by landlords to evict tenants, in 2013. King County provides a unique and useful backdrop for studying evictions. As one of the fastest growing counties in the US, King County has a diverse range of neighborhoods and socio-demographic compositions that captures rapidly changing conditions in a fast-paced economy (Fowler, 2016).

In King County, the median household income was $75,302 between 2011 and 2015. For Whites, the median household income was $80k, where 79% of males and 71% of females were employed. Black households report the lowest median household income below $39k with 65% of males and 61% of females being employed. Black and Latino households rent at higher rates (57% and 52%) than Whites (30%) making them more vulnerable to evictions. According to yearly reports from the Department of Housing and Urban Development, low-income status for a family of four, is between low-income ($64,000) and extremely low-income ($26,000) for the county (Housing and Urban Development, 2013).

4.4.1 Dependent & Independent Variables

The dependent variable is the count of unlawful detainers in each tract for the year 2013. To operationalize neighborhood change, the independent variables consist of eight tract level change-scores ($t_{2i} - t_{1i} = \Delta_i$) between 2000 and 2015 using median rent (in $1,000s); percent in poverty;

the proportion of adults who are college educated; proportion of the population that is Asian, Latino, and Black;[1] total population size (in 1,000s); and the proportion of individuals that moved into the respective tract within the last five years. To account for interactions in the models, I center the variables to the county median of the respective variable, which does not change the coefficient or the standard error, however it does change the intercept. This provides a more meaningful interpretation when accounting for controls at zero. For example, for an un-centered rent variable, holding rent at zero would mean $0 rent, which is a meaningless interpretation given there are no tracts with zero rent. Now, the interpretation of each variable is controlling for each of the other variables held at their median.

Independent variables are drawn from the US Decennial Census in 2000 and the 2011 to 2015 American Community Survey. The only exception is median rent between 2011 and 2015, which is drawn from Zillows 2013 estimates. Given the sampling strategy of the ACS, Zillow rent provides a more accurate rental estimation. All dollar amounts are converted to 2015 dollars. The explanatory variables of education and rent operationalize socioeconomic and housing characteristics of the tract.[2] Increases in population, housing units, and the new movers operationalizes demand for the area controlling for varying effects for Latino and Black changes in the tract. It is worth noting that these control variables are likely to be related to gentrification. For example, increases in rent and SES may be associated with areas going through gentrification. Likewise, areas seeing decreasing Black populations are commonly identified with gentrification. However, as mentioned before, measures of gentrification require more complex measures that mix ground-level observations of aesthetic, infrastructure, and housing improvements with various census measures like the

---

[1]White tract change composition introduces extremely high multicollinearity and is therefore omitted from the models.

[2]Median family income and home values were assessed in preliminary models, however these inclusions introduced high multicollinearity in the model due to the high correlation between education and income, and rent and home value. Therefore, income and home values are excluded where education and rent are proxies for socioeconomic status and housing market effects. Future research will accommodate these variables in a more robust manner.

ones presented in this study. Studies that rely solely on census data tend to misclassify whether an area is gentrifying or not because they ignore areas that experienced prolonged disadvantage. Studies that have more accurately captured gentrification take these issues into account and created categorical identifiers of gentrifying versus non-gentrifying neighborhoods (Kreager et al., 2011; Wyly and Hammel, 2004). However, these categorical identifiers have not been updated for the current decade. Regardless, the purpose of this study is to be more inclusive towards different types of neighborhood change that are not strictly confined to the definition of gentrification.

4.5 Analytical Strategy

The models use a negative binomial regression on the count of evictions for each tract. The count of evictions is over-dispersed with a mean of 12.9 and variance of 226.7. Using these data on an OLS model violates several assumptions and, therefore, a negative binomial model (NB) model is used to help deal with over-dispersion found within the count DV. Prior research on crime counts has popularized the use of the negative binomial when examining counts where there is often over-dispersion due to the clustering of events that occur in some areas more frequently than others (Gelman et al., 2007). Research on historical data for lynchings has also found that the use of a negative binomial can be a better model for over-dispersed data as compared to Poisson and modified Poisson regressions (Beck and Tolnay, 1995).

The preference of NB over the familiar ordinary least squares linear model (LM) is due to the failure of several assumptions required by the LM. First, the dependent variable should be continuous whereas count data are discrete. Second, count variables are truncated at zero where the LM prefers non-truncated variables. Third, the LM is best used with a normally, or symmetric, distribution whereas count data have a distinct asymmetry (Beck and Tolnay, 1995).[3] While logging

[3] Another model that could be used is a zero-inflated negative binomial which separates the data into two categories, zero evictions and non-zero evictions. This approach is best used when there is an excess number of zeros, however, there are only 25 zero counts in the data, which is about 6% of the 397 tracts observed.

the counts of evictions would alleviate some of these issues, a number of sampling zeros in the eviction count data produces non-number outputs and eliminates 6% of the dataset.

An alternative to the LM approach is to model count data along the Poisson distribution, which analyzes discrete events that are randomly and independently distributed across time or space. However, one of the main properties of the Poisson is that there should be no over-dispersion where the mean should equal the variance. In the presence of over-dispersion, the Poisson distribution will provide misleading associations, leading to underestimated standard errors and optimistic t-ratios (Beck and Tolnay, 1995; Gelman and Hill, 2007). The Quasi-Poisson (or modified Poisson) family of the general linear model can accommodate over-dispersion by shifting the standard errors upwards by assuming the variance is a linear function of the mean and producing a fit that follows along the over-dispersed data. The negative binomial regression follows a similar principle but shifts the standard errors using a quadratic function to better fit the over-dispersed data. Testing model fits of the Poisson, Quasi-Poisson, and negative binomial of the full final model for this study shows a strong preference for the negative binomial over the other two (see Table 4.3 for comparative results of Poisson, Quasi-Poisson, and Negative Binomial).

The dependent variable of the model is the count of evictions, however, a rate of evictions is a preferred interpretation over the raw count for two main reasons. One, renters are the population at risk of eviction and a rate helps determine the risk ratio with different tracts. Two, eviction counts fall within tracts, which is a unit of observation that features varying boundary and population sizes. A rate of the dependent variable accommodates these characteristics providing an outcome that is proportional to these varying dimensions. To interpret these findings as rates, a logged offset of all renters[4] is included on the right-hand side of the equation. For the negative binomial, this logged

[4]Arguably, not all renters are at risk of eviction and, therefore, a denominator of renters at risk could be used in lieu of all renters (e.g., renters that contribute 30% to 50% of their income to rent). However, for this study, I choose all renters for these reasons: First, my main intention for this analysis is to evaluate the overall ecological understanding of evictions, like an overall rate of mortality in a country, where using all renters achieves this goal. Decomposing renters by rent burden starts to delve into individual level assumptions using aggregate level data (i.e., ecological

offset predictor becomes the denominator exposure (renters) and the count of contested evictions becomes the numerator. The rate for the negative binomial model starts with this structure

$$log(\frac{y}{z}) = \beta' X_n$$

where y is the count of evictions and z is the count of renters for the given tract and $\beta' X_n$ is the respective input. This is then written as

$$log(y) - log(z) = \beta' X_n$$

$$log(y) = \beta' X_n + log(z)$$

where the logged exposure r is now an offset on the right-hand side of the equation. The subsequent coefficients of this model are then interpreted as the exponential rate of evictions per unit exposure (renters) for the given median centered explanatory variable.

4.6 Results

4.6.1 Descriptive Statistics

Table 4.1 presents the tract level descriptive statistics for the main dependent and independent variables. The average number of evictions in King County tracts was about 13 (median = 8) with a range from 0 to 93 evictions. Eviction rates averaged about 1.5% ranging from 0% to 11%. A little over 1/3rd of all occupied households were renters (37%) ranging from 2% to 97% within a

fallacy) and requires different questions about the population, which strays from a broader ecological framing of this work. Second, analysis using renters with 30% and 50% rent burden did not significantly change the findings. There was a slight increase in the overall eviction rate, however, using a 30% cutoff is exceptionally conservative given that past research shows evicted tenants contribute upwards of 80%-90% of their income to rent. The 50% cutoff also introduced strange outcomes through multicollinearity. Third, not all evictions are due to rent burden, where some households may have the means to pay but simply do not for some reason. To start analyzing different types of renters would require individual level data that is not available at this time.

tract. Tracts saw an overall increase in socioeconomic status with education seeing median increase of 7% and a median increase of rent by $684. Poverty in 2000 was 6% and increased to 9% between 2011 and 2015. In addition, King County experienced an overall population increase with a median of 536 more people per tract, with marginal increases in the Asian and Latino households between 1.2% and 2.3%. However, tracts saw a slight decrease in the Black population (- 0.2%) and a decrease in the proportion of new movers in 2011 to 2015 as compared to 2000 (- 17%). The lower mover rate between 2000 and 2015 may be a reflection of the effects of the housing crisis in the mid-2000s.

Figure 4.1 presents the spatial patterns of rent, education, and population shifts of Black and Latino residents from 2000 to 2015. The color scheme shows whether the respective variable is above (red) or below (blue) the county median in that tract while the legend provides the actual values of change within the 15-year period. Starting at the top left, median poverty saw a range of change from -22% decline to 35% increase with a county median of positive 2% change. Overall, Seattle and parts of Bellevue saw the largest declines in poverty while South King County and north of Seattle saw most of the increases in poverty. Education (top right) shows an opposite trend. Increases above the county education median change range from positive 7% to 40% while below median areas saw small increases up to 7% and declines down to negative 10%. Median rent (middle left) converted to 2015 dollars saw an overall increase from 2000 to 2015 where Seattle and Bellevue saw increases above the median change ($684) with increases ranging from $700 (light red) to $3,700 (dark red). South King County saw marginal increases mostly ranging from $100 to $700 increases with a few tracts seeing decreases of minus $100. Education and rent saw similar spatial trends in increases and declines with a few exceptions. Rent and education shifts show that higher SES increased in Seattle and Bellevue cores where rents also increased, while declines in education occurred largely towards South King County and parts of North King County.

Movers in the past 5-years (middle right) involves destinations for both high and low SES individuals occupying different parts of the region. The recent new movers between 2000 and 2015 had a lower proportion of new movers than between 1995 and 2000. Areas with some positive increase the latter period (dark red) occurred in pockets across Seattle, parts of Bellevue and some in South King County. Tracts with movers above the median change fall mostly within Seattle and Bellevue city limits and westerly portions of South King County. The lowest percentages of movers are in more suburban areas suggesting possible long-term residence among households in these areas. King Countys large growth both economically and population wise would mean that these lower-mover areas are not necessarily representing decline but possibly more stability (i.e., long term residents who may own their home over ten years). Examining the location of unlawful detainers (center left map) shows most of the clustering occurring around areas that saw above median changes in the movers. However, further analysis should be done to disentangle this phenomenon. Finally, both Black and Latino populations saw increases in South King County and declines in Seattle, nearly opposite of rent and education trends of increase and decline. Prior research suggests that Black households, in particular, have been displaced outside of South Seattle and have been relocating to South King County due to mechanisms of gentrification (Fowler, 2016; McGee, 2007).

4.6.2 Change Model Results

Table 4.2 lists results of five, within tract, change-score negative binomial models for socioeconomic status, housing, and population change. Model 1 examines the centered baseline 2000 coefficients for rent, education, poverty, racial composition, population growth, and new movers. The intercept provides the baseline eviction rate of $e^{-4.33} = 0.014$. Education and poverty in 2000 are both negative meaning that tracts that had higher education and higher poverty in 2000 had a lower eviction rate in 2013 net of other 2000 period effects. Though the negative effect of poverty in 2000 is counter to the hypothesis that it should be positive, its significance disappears after

Model 3. The proportion of new movers between 1995 to 2000 had a positive relationship with 2013 evictions, but loses significance by Model 4.

Model 2 introduces the change in education and poverty net of 2000 effects with change in education having a highly significant negative effect all the way through to model 5, fitting our hypothesis that tracts seeing increases in SES see lower eviction rates in 2013. Change in poverty is non-significant through all the models. Model 3 adds rent and the interaction of rent and education. The main effect of rent is not significant, however its interaction with education is, which shows that each are dependent on each other with a negative significant interaction effect through to Model 5 net of other controls. For a 1 unit increase in rent there is about a 98% declining difference in education. This gives some evidence toward the rent hypothesis on the negative relationship, but it is dependent on education.

Model 4 introduces change in population and new movers as well as the interaction between the two where all three effects are significant through Model 5. Population change has a positive relationship that fits the hypothesis that crowding is related to increases in evictions by about 5%. Change in new movers has a stronger negative relationship while the interaction of population and mover change has a positive significant relationship. Finally, Model 5 adds the change in race showing significant positive relationships for Black and Latino change with multiplicative effects of $e^{1.91} = 6.75$ and $e^{1.34} = 3.82$ respectively. Education and new movers have relatively large negative multiplicative effects of 0.11 and 0.22 respectively. For the 2000 coefficients, education and the Asian proportion are negative. This means that areas that started with high education, as well as tracts that had increases in education, both had lower rates of eviction in 2013. The 2000 proportion black coefficient interpreted with the positive relationship of change in black population suggests that areas that had higher numbers of residents who were Black had lower evictions, while areas that saw increases in the Black population saw higher rates of eviction.

The main takeaways from this final model is that tracts with increases in education and new movers have a protective effect against evictions. The other main effect of interest is that increases in Black and Latino populations increases the risk of eviction in the respective neighborhood. However, Poverty doesnt seem to have a major effect in any of the models. It is possible that some other economic predictor may better explain the relationship of tract income and evictions. Observing the maps from Figure 4.1 shows that tracts that saw increases in these two groups (mostly South King County) saw substantial increases in poverty at the same time. Again, it is important to refrain from ecological fallacy by making assumptions about household level economic circumstances without individual level data. However, we can say that large increase in the Black and Latino population spatially coincide with increases in poverty and declines in education, possibly suggesting broader issues with where these populations move to.

4.6.3 Predicted Probability Plots

To help explain these effects, Figure 4.2 provides the predicted probability of changes in Black, Latino, mover, and education effects on the rate of evictions. The top four plots provide the expected eviction rate along with 95 percent confidence intervals for each respective variable at different values while holding all other variables at their median value. The bottom four plots show the predicted count of evictions and include a fitted trend line to show the average trajectory for the given value. The x-axis features the actual proportion changes for each variable and is confined between the 5% and 95% quantiles of the respective change distribution.

Black population growth has an overall positive relationship with a predicted rate of eviction of 0.012 at the median, a high of about 0.015 at about 8-percenteage point growth in the population, and about 0.01 around 8-percentage point decrease in Black residents. The predicted count of evictions is about 10 for tracts that see 8% decreases and up to just under 13 evictions when the Black population grows over 8-percentage points above zero. Latino growth sees a similar positive trend that falls just below the Black rates, starting with a rate of about 0.011 with a 5-

percentage point loss of Latino residents and upwards to 0.015 rate with growth increases above 15-percentage points. Counts in these neighborhoods range around 10 evictions with declines of -.025 and up to about 13 evictions with above a 15-percentage point gain. The proportion of new movers and education both have a negative relationship. The proportion of new movers mostly declined between 2000 and 2015 with eviction rates ranging from about 0.015 with more than 30-percentage points decrease to about 0.007 with about 10-percentage point increase. The proportion of residents with a bachelors degree or higher mostly increased in King County tracts with a median of about 7.1-precentage point gain and eviction rates from 0.016 with 5-percentage point loss of education and about 0.008 with education gains around 20-percentage points. Both education and new movers saw a slightly declining count of evictions where new movers range from 11 to about 10 evictions and education from 10 to about 9.

4.7 Conclusion

Research on evictions expands the investigation of residential mobility by examining the forced removal of low-income households through rising housing burden. The primary focus, thus far, revolves around household-level predictors, such as low wages and welfare support that fail to compete with annually rising rents. However, little is known about the spatial characteristics that are associated with evictions and increasing demand in a neighborhood that may pressure low-income families out of certain neighborhoods. This analysis fills the gap by examining housing market, demographic, and socioeconomic neighborhood changes that are associated with eviction rates at the end of a tracts transition from 2000 to 2015 in King County, WA. Results show that evictions are lower in neighborhoods with increasing new movers and education while increases in Black and Latino residents coincide with higher rates of eviction in 2013. Interestingly, poverty did not have a significant effect net of all other predictors and the increase in rent, one of the key structural constraints leading to eviction in prior research, is not significant when controlling for socioeconomic and population dynamics. However, it is conditional for increases in education where the interaction is negative in relationship with eviction rates and strengthens the already negative education effect. Higher evictions in areas with decreasing SES and rent reinforces prior findings that evictions occur in the most disadvantaged neighborhoods where SES and rent are low.

The higher eviction rate among increasing Black and Latino populations and decreasing SES suggests that forced removal of households is largely related to the changes in socioeconomic class and racial composition, both intertwined elements of a legacy of structural inequality of the region. By 1960, Black residents in Seattle were highly segregated near downtown at a time when urban neighborhoods were the most disadvantaged spaces. Exclusion from home lending, education, and decent employment led to high rates of renting among Black households. The economic boom in the 1990s led to increasing gentrification of segregated spaces and subsequent displacement of Black households to South King County (McGee, 2007). Part of this early effect is observed in the results where the Black composition in 2000 was highly significant and positive with a multiplicative effect of 8.24 net of all other variables. This means that tracts that had a larger number or residents who were Black in 2000 see a high rate of evictions in 2013. At the same time, the Latino population increased in the south creating the diverse neighborhoods we see today. By 2013 family incomes did not improve for Black and Latino households with earnings falling at a median of $38,000 and $50,000, which, by HUD standards for a family of four, hovers between low-income ($64,000) and extremely low-income ($26,000) for the county (Housing and Urban Development, 2013). These trajectories lend evidence to why we might see higher rates of eviction in neighborhoods with increasing Black and Latino populations.

There are several limitations to this study. First, SES is operationalized largely by education and poverty due to the high multicollinearity of median income on most of the explanatory variables in the analysis. Future research should consider other economic factors and consider ways to include neighborhood income as a predictor to better understand socioeconomic relationships to evictions.

Perhaps disaggregating income by race might be a better fit as there are distinct differences in group income structures. Second, the lack of longitudinal evictions data greatly limits the conversation on causal inference related to changes in the neighborhood. For example, we would expect that areas that see an increase from low to high rent and SES should positively predict rates of evictions at earlier periods due to increasing demand. Third, it is still unclear to what degree gentrification and steady increases in demand affect evictions. The results of what is happening in South King County now, where there are high rates of eviction and high disadvantage, could be similar to events that occurred decades before in South Seattle where there are now low eviction rates. In other words, South King County could be at the beginning stages of gentrifying processes that South Seattle already experienced. Fourth, the simplified analysis of housing demand in this study would benefit from a more exhaustive classification of demand that includes home values and other related characteristics in addition to the demographic and socioeconomic characteristics. Lastly, qualitative research among tenants and landlords on why households have been removed and where they ended up would greatly improve our sociological understanding of neighborhood and housing effects in low-income neighborhoods.

Table 4.1: Descriptive Statistics for Dependent & Independent Variables

	Median	Average	Range
Number of Evictions in 2013	8	13	0 to 93
Eviction Rate	1%	6%	0% to 11%
Number of Renters b/w 2011 and 2015	35%	37%	2% to 97%
	2000 Median Tract Value	2011 to 2015 Median Tract Value	2000 to 2015 Median Change Score
Percent of the population with a Bachelor's degree or higher	38.6%	47.3%	7.1%
Median rent (in 2015 dollars)	$1,087	$1,805	$684
Asian median	10.3%	12.3%	1.2%
Latino median	4.2%	6.3%	2.3%
Black median	3.3%	3.2%	-0.2%
Population median count	4,220	5,022	536
Percent in poverty	6%	9%	2%
Percent of owner and renter occupied households that moved into the tract within the last 5 years	52.3%	34.7%	-17.5%

Data source: ACS 2010-2014, Zillow tract-level rent data, & King County Courthouse Unlawful Detainer Cases for 2013

Table 4.2: Negative Binomial Neighborhood Change Score Analysis of the King County Eviction Rate (2013)

	Model 1 Baseline 2000	Model 2 Δ SES	Model 3 Δ Houseing Market	Model 4 Δ Pop. Growth	Model 5 Δ Race Type
(Intercept)	$-4.33\ (0.04)^{***}$	$-4.35\ (0.04)^{***}$	$-4.35\ (0.04)^{***}$	$-4.39\ (0.04)^{***}$	$-4.42\ (0.05)^{***}$
2000 Rent (2015 Dollars)	$0.16\ (0.17)$	$0.29\ (0.16)^{\dagger}$	$0.42\ (0.19)^{*}$	$0.30\ (0.19)$	$0.26\ (0.20)$
2000 Education (BA+)	$-3.58\ (0.26)^{***}$	$-3.28\ (0.25)^{***}$	$-3.73\ (0.34)^{***}$	$-3.48\ (0.35)^{***}$	$-3.13\ (0.38)^{***}$
2000 Prop. Persons in Poverty	$-1.93\ (0.69)^{**}$	$-1.19\ (0.66)^{\dagger}$	$-0.97\ (0.65)$	$-0.46\ (0.67)$	$-0.38\ (0.67)$
2000 Prop. Asian	$-0.51\ (0.39)$	$-0.58\ (0.37)$	$-0.81\ (0.37)^{*}$	$-0.72\ (0.36)^{*}$	$-0.90\ (0.37)^{*}$
2000 Prop. Latino	$-0.38\ (1.01)$	$-0.31\ (0.98)$	$-0.68\ (0.96)$	$-0.53\ (0.95)$	$-0.60\ (0.95)$
2000 Prop. Black	$0.84\ (0.53)$	$1.10\ (0.51)^{*}$	$1.34\ (0.50)^{**}$	$1.34\ (0.50)^{**}$	$2.11\ (0.59)^{***}$
2000 Population Size	$0.03\ (0.02)$	$-0.01\ (0.02)$	$-0.01\ (0.02)$	$0.02\ (0.02)$	$0.02\ (0.02)$
2000 Prop. New Movers 1995 - 2000	$0.78\ (0.32)^{*}$	$0.71\ (0.30)^{*}$	$0.85\ (0.31)^{**}$	$0.42\ (0.35)$	$0.22\ (0.37)$
Δ Education 2000 - 2015		$-2.91\ (0.45)^{***}$	$-2.85\ (0.45)^{***}$	$-2.87\ (0.46)^{***}$	$-2.23\ (0.52)^{***}$
Δ Poverty 2000 - 2015		$-0.50\ (0.58)$	$-0.57\ (0.57)$	$-0.40\ (0.58)$	$-0.77\ (0.59)$
Δ Rent 2000 - 2015			$0.16\ (0.13)$	$0.11\ (0.13)$	$0.11\ (0.13)$
Δ Population 2000 - 2015				$0.05\ (0.03)^{*}$	$0.05\ (0.03)^{\dagger}$
Δ New Movers				$-1.31\ (0.48)^{**}$	$-1.48\ (0.48)^{**}$
Δ Prop. Asian					$0.00\ (0.50)$
Δ Prop. Latino					$1.34\ (0.68)^{\dagger}$
Δ Prop. Black					$1.91\ (0.76)^{*}$
Δ Education * Δ Rent			$-4.01\ (1.31)^{**}$	$-3.71\ (1.30)^{**}$	$-3.75\ (1.29)^{**}$
Δ Population * Δ New Movers				$0.42\ (0.20)^{*}$	$0.43\ (0.20)^{*}$
AIC	2434.39	2395.81	2388.01	2379.48	2377.61
BIC	2474.23	2443.62	2443.78	2447.21	2457.29
Log Likelihood	−1207.20	−1185.91	−1180.00	−1172.74	−1168.80
Deviance	438.02	439.36	438.68	437.05	436.06
Num. obs.	397	397	397	397	397

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Table 4.3: Comparison of Poisson, Quasi-Poisson, and Negative Binomial Models

	Poisson	Quasi-Poisson	Negative Binomial
(Intercept)	$-4.46\ (0.03)^{***}$	$-4.46\ (0.05)^{***}$	$-4.42\ (0.05)^{***}$
2000 Rent (2015 Dollars)	$0.50\ (0.12)^{***}$	$0.50\ (0.25)^{*}$	$0.26\ (0.20)$
2000 Education (BA+)	$-3.25\ (0.20)^{***}$	$-3.25\ (0.42)^{***}$	$-3.13\ (0.38)^{***}$
2000 Prop. Persons in Poverty	$-0.35\ (0.33)$	$-0.35\ (0.68)$	$-0.38\ (0.67)$
2000 Prop. Asian	$-1.05\ (0.19)^{***}$	$-1.05\ (0.39)^{**}$	$-0.90\ (0.37)^{*}$
2000 Prop. Latino	$-0.42\ (0.42)$	$-0.42\ (0.87)$	$-0.60\ (0.95)$
2000 Prop. Black	$2.02\ (0.26)^{***}$	$2.02\ (0.53)^{***}$	$2.11\ (0.59)^{***}$
2000 Population Size	$0.02\ (0.01)$	$0.02\ (0.02)$	$0.02\ (0.02)$
2000 Prop. New Movers 1995 - 2000	$0.47\ (0.18)^{**}$	$0.47\ (0.37)$	$0.22\ (0.37)$
Δ Education 2000 - 2015	$-2.59\ (0.24)^{***}$	$-2.59\ (0.50)^{***}$	$-2.23\ (0.52)^{***}$
Δ Poverty 2000 - 2015	$-0.97\ (0.25)^{***}$	$-0.97\ (0.52)^{\dagger}$	$-0.77\ (0.59)$
Δ Rent 2000 - 2015	$0.16\ (0.08)^{*}$	$0.16\ (0.16)$	$0.11\ (0.13)$
Δ Population 2000 - 2015	$0.06\ (0.01)^{***}$	$0.06\ (0.03)^{*}$	$0.05\ (0.03)^{\dagger}$
Δ New Movers	$-0.92\ (0.23)^{***}$	$-0.92\ (0.49)^{\dagger}$	$-1.48\ (0.48)^{**}$
Δ Prop. Asian	$-0.10\ (0.25)$	$-0.10\ (0.52)$	$0.00\ (0.50)$
Δ Prop. Latino	$1.39\ (0.30)^{***}$	$1.39\ (0.62)^{*}$	$1.34\ (0.68)^{\dagger}$
Δ Prop. Black	$1.44\ (0.33)^{***}$	$1.44\ (0.69)^{*}$	$1.91\ (0.76)^{*}$
Δ Education * Δ Rent	$-3.60\ (0.65)^{***}$	$-3.60\ (1.35)^{**}$	$-3.75\ (1.29)^{**}$
Δ Population * Δ New Movers	$0.17\ (0.09)^{*}$	$0.17\ (0.18)$	$0.43\ (0.20)^{*}$
AIC	2938.35		2377.61
BIC	3014.05		2457.29
Log Likelihood	-1450.18		-1168.80
Deviance	1432.43	1432.43	436.06
Num. obs.	397	397	397

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, $^{\dagger}p < 0.1$

Standard errors are in parentheses. The Poisson, Quasi-Poisson, and negative binomial lead to somewhat similar results with variation in the p-values. However, the AIC, BIC, and deviance all point to the negative binomial as the better fitting model. Also, a log-likelihood test between the Poisson and the negative binomial are statistically significant by conventional means.

Figure 4.1: Map of Change Scores for Centered Rent, Education, and Population Between 2000 to 2015

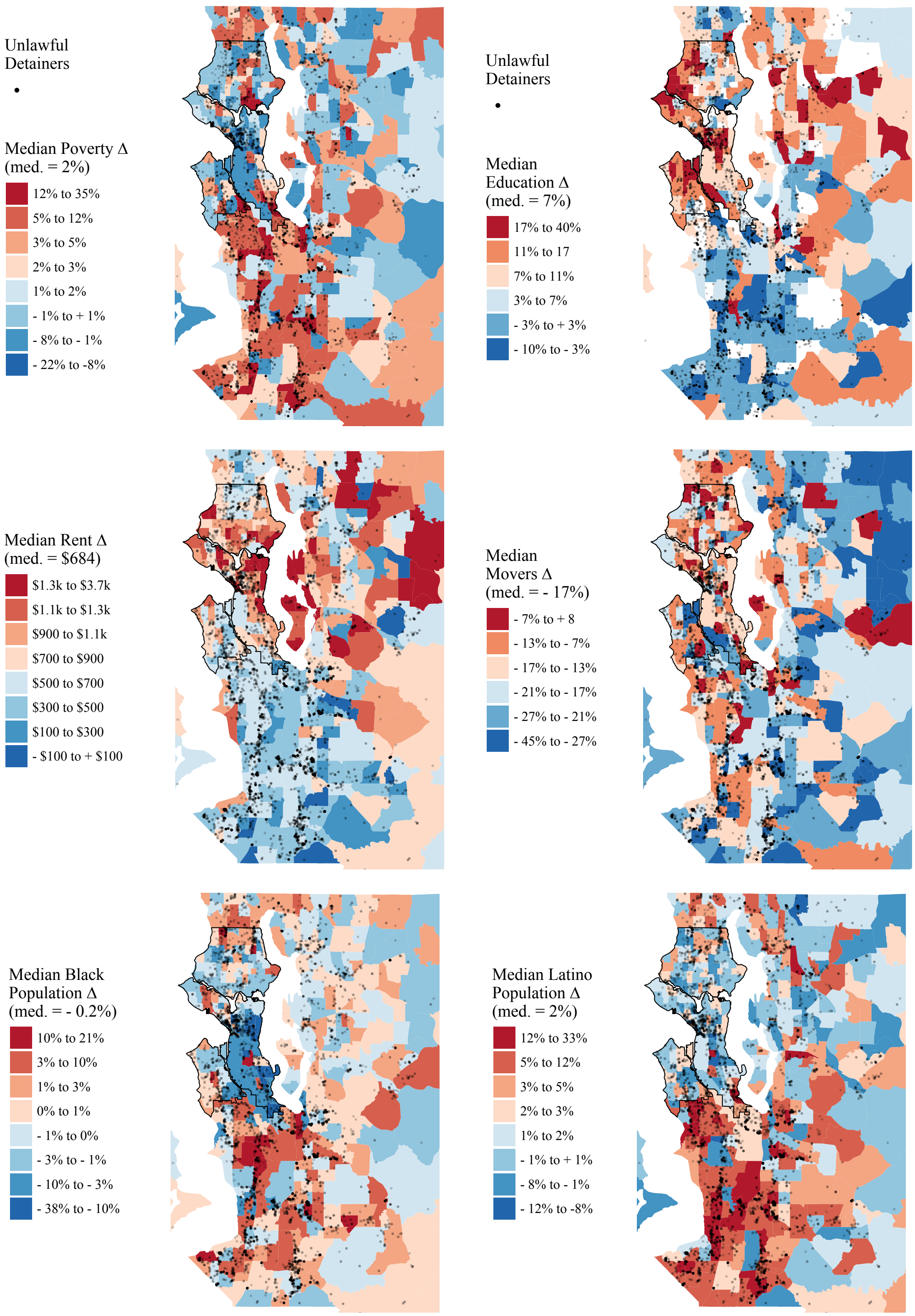
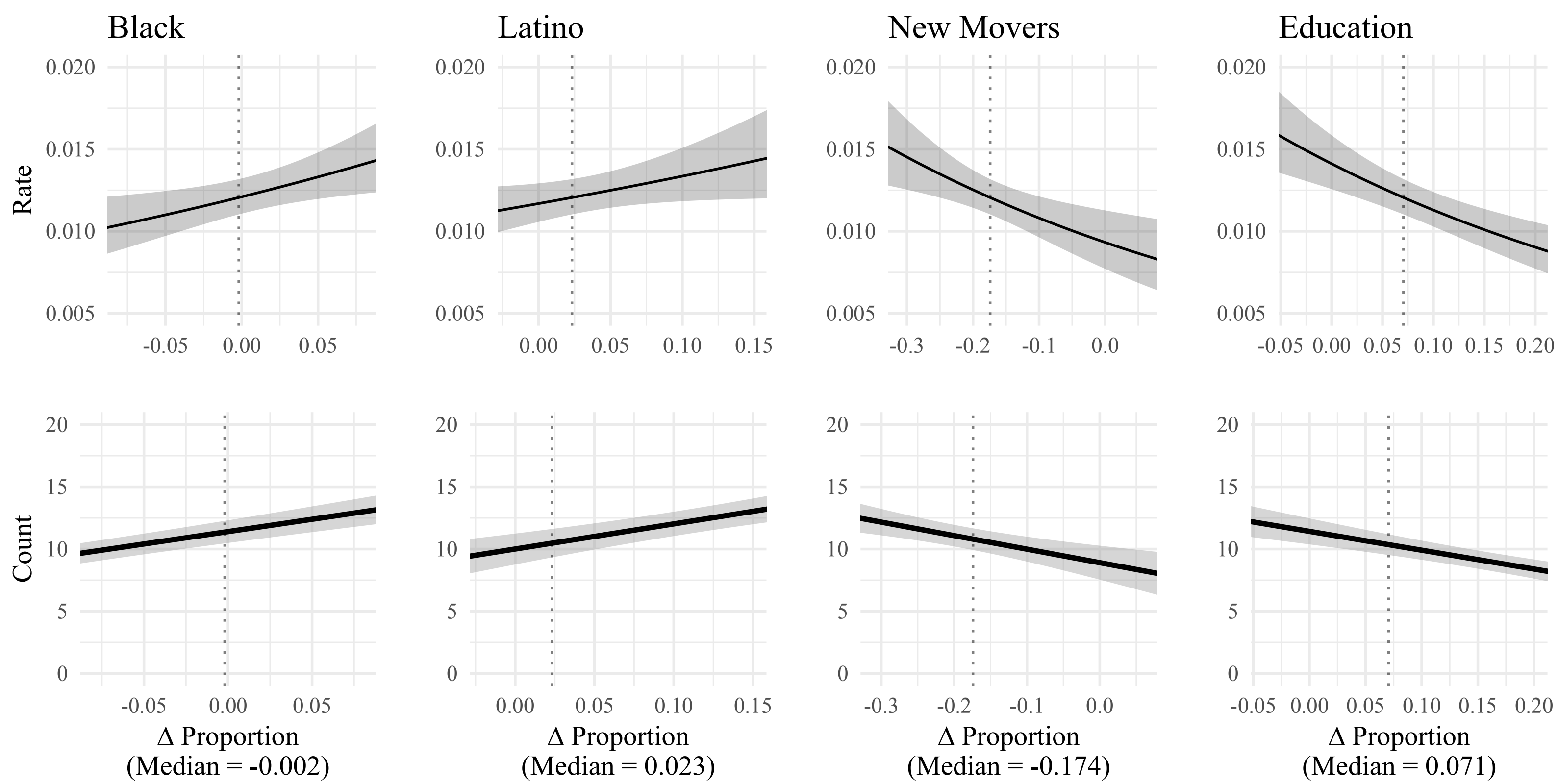


Figure 4.2: Predicted Probability of Evictions & Change in Black, Latino, New Movers, & Education for the Full Negative Binomial Model 5



Chapter 5

CONCLUSION

Prior findings on household level mechanisms of evictions were right: the rental market is a key structural constraint that increases evictions. However, it is not simply the economic side of the market or cost, but more largely the properties of population growth and demand that commodifies space and restricts access to those that have historically benefited from economic growth. These benefactors are divided along racial lines, where the historical growth of the city sorted ethno-racial groups into advantaged and disadvantaged spaces, leading to generational improvement or hardship depending on where they lived. The ecological evaluation of evictions reinforces the fact that place matters when it comes to household opportunity.

The first chapter of this dissertation demonstrates this racial disparity in evictions where Black households experience eviction rates four times higher than whites, and five times higher when comparing Black-female headed households to White-male headed households. Spatial concentrations of evictions occur mostly in neighborhoods that are further away from economic centers, with higher rent-burden, the lowest rent, and in racially diverse or mostly minority neighborhoods. However, among racial groups, we see that Black households, who consist of only 9% of renting households, outpace all other groups by between two and five times in evictions.

Chapter two examines the local and extra-local effects of rent, poverty, and racial composition of the neighborhood. At the local level, poverty, diversity, White-Black, and White-Latino neighborhoods positively predict eviction concentrations, net of all variables. However, extra-local dynamics have the greatest effect on evictions. Living near low-poverty and/or affordable (low-rent) neighborhoods greatly increases the likelihood of evictions. Theory posits that landlords will file for eviction if the likelihood of replacing a low-income tenant with a higher-earning one is high. Therefore, nearby conditions could forecast whether this is likely or not depending on nearby market conditions and demand. To compound this, affordable spaces are a scarce commodity in King County due to rapidly rising housing costs, forcing large numbers of households to scramble for housing within their price-point. Finally, chapter three measures neighborhood change preceding evictions in 2013. Again, we see significant racial differences where increases in the Black and Latino population lead to higher rates of evictions while increases in new movers and education are associated with substantially lower rates of eviction.

These findings help improve our understanding of housing instability, racial stratification, and strengthens our understanding of the ecology of evictions, which is tied closely to the sociodemographic and racial development of the city. Net of rent, poverty, racial composition, and population growth, the primary neighborhood features that protect against eviction (i.e., has the lowest likelihood of eviction) are tracts that are white segregated, low-poverty, high education, the least affordable, and are the most preferred destinations for new movers. On many levels, these five neighborhood features are the least accessible to non-Whites as they require large resources and privileges that have been protected through a legacy of discriminatory policy-making and lending practices over the years. This legacy has led to an over-representation of renting among Black and Latino households that live in areas that experience greater disadvantage, economic inequality, and potentially higher housing instability.

What this research highlights is the need to move beyond simply examining local conditions and to account for both nearby effects as well as the historical context of the metro being observed. In other words, scholars need to intentionally incorporate the unique features of each metropolitan area when examining evictions and stratification. For example, Milwaukee has a large Black population and high poverty rates, creating some specific contextual results such as how race is not a significant predictor of who gets evicted at the household level (Desmond and Gershenson, 2017).

However, in King County, an area with only 6% Black, race is highly related to evictions both at the household and neighborhood level. Furthermore, contexts of neighborhood change in racial and socioeconomic stratification predict eviction rates while housing markets have a lesser effect. Understanding these markets is incredibly important in both the development of hypotheses and interpreting results as many of these findings rely on understanding what is happening in the city.

One prime example of why understanding the study area is important is the interesting finding in this analysis is the negative relationship of rent. At face-value, this is somewhat perplexing as one would assume that increases in rent would coincide with increases in evictions. However, that was not the case. Largely, I believe that this relationship reinforces the previous point that the historical context of a metro plays a vital role in interpreting these types of effects. For one, King Countys massive increase in housing cost has sent many households scrambling to find affordable housing. Second, with over 400 new arrivals per week, growth and crowding is only increasing this effect, making affordable spaces an incredibly rare commodity. Lastly, low-income households may stay beyond their due date for eviction in hopes to work out a deal, have time to find a better place, or simply because they cant afford anywhere else. The time and effort to find an affordable unit takes time when supply is low. It takes even more time if there are necessary criteria such as extra rooms for children in the household or special needs due to physical or mental disability.

On this point, the study is limited to measuring only contested evictions (i.e., evictions that ended up going to court as the household stayed beyond their posted eviction date), which may have a unique effect on the overall spatial patterns of evictions. As mentioned before, the scarcity of affordable spaces due to high housing costs in the region may force households to contest evictions, staying beyond their due date of eviction because they are unable to find affordable housing in the county that matches their needs, or they simply feel their eviction is unwarranted and want to fight it. However, without individual level data, this is impossible to answer. Also, there is no reliable data on non-contested evictions. If we had these data, we could get at a better understanding of the overall landscape of evictions. Future research should make this a top priority as evictions research not only speaks to housing insecurity but also provides more detailed migration dynamics that much of the literature hasnt been able to examine.

This research suffers from a variety of other limitations. For one, variable selection was difficult given the little research on this particular topic. The importance of racial composition was relatively obvious, however, trying to capture ecological demand and socioeconomics was more challenging. Multicollinearity was a difficult problem to overcome as income and mostly White neighborhoods were highly correlated with many variables. In addition, other data could help improve the demand hypothesis such as housing value and the built environment. Lastly, modeling would benefit from a principal component analysis given the multicollinearity of important variables. Future research needs to consider other methods and explore more detailed data that can speak to market and demand characteristics that would better describe these mechanisms.

Another limitation is the lack of individual level data available for the eviction records. Race was estimated using a Bayesian process, which, while demonstrated to be highly accurate, does not guarantee exact identification for all individuals. Also, the data used in this study do not include detailed information about the reasons for eviction. Court records have reason for eviction and it would be highly beneficial to include this in the analysis. Lastly, the lack of longitudinal data greatly limited predicting which change variables create more evictions. Figure 2.1 shows how the UD count in 2013 is the lowest over the past 10 years. Given the shift of the Black population over the past forty years in King County (see Figure 2.9) and the high representation of Black tenants in the household level 2013 data, earlier years of eviction data may include even higher number of Black tenants given this was a period of economic crisis overall and physical mobility for Black households. One reason is that the housing market crash during the 2000s had a huge impact on Black and Latino households (Hall et al., 2015). The high eviction counts right before 2008 could be a direct result of that economic event and the disparity of who gets evicted during that time could have been greater than what we see today.

Regarding future research, I immediately plan to examine racial disparities in evictions. The Bayesian estimation provides a unique opportunity to try and disentangle which household types see higher rates of eviction and what neighborhood characteristics might influence this. Another future agenda is to improve the current evictions data with the expansion of years and hopefully reasons why evictions were filed. The longitudinal aspect would provide incredible insight into what broader mechanisms are impacting evictions, both at the neighborhood level and at the broader county level. Finally, future research would benefit from an analysis that examines the policies that may be associated with evictions. For example, was there a policy change in 2006 that led to the decline in evictions? Was it directly related to evictions or was it a housing market effect that might have led to the decline in evictions, such as opening up zoning to developers or multi-family homes? These questions would help inform not only scholarly research on the topic, but help inform housing policy on a broader scale.

BIBLIOGRAPHY

Amato, Rebecca and Jeffrey. T. Manuel. 2012. "Using Radical Public History Tours to Reframe Urban Crime." *Radical History Review* 2012:212–224.

Aratani, Yumiko, Michelle Chau, Vanessa R. Wight, and Sophia Addy. 2011. "Rent Burden, Housing Subsidies and the Well-being of Children and Youth." Technical Report November, The National Center for Children in Poverty, New York.

Atkinson, Rowland. 2002. "Does Gentrification Help or Harm Urban Neighbourhoods? An Assessment of the Evidence-Base in the Context of the New Urban Agenda." Technical Report June, ESRC Centre for Neighbourhood Research.

Barton, Michael S. and Colin P. Gruner. 2016. "A Theoretical Explanation of the Influence of Gentrification on Neighborhood Crime." *Deviant Behavior* 37:30–46.

Beck, E. M. and Stewart E. Tolnay. 1995. "Analyzing Historical Count Data." *Historical Methods* 28:125.

Bivand, Roger S., Edzer Pebesma, and Virgilio Gómez-Rubio. 2013. *Applied Spatial Data Analysis with R*. New York: Springer, second edition.

Blevins, Cameron and Lincoln Mullen. 2015. "Jane, John … Leslie? A Historical Method for Algorithmic Gender Prediction." *Digital Humanities Quarterly* 9:1–19.

Braga, Anthony A. and Brenda J. Bond. 2008. "Policing Crime and Disorder Hotspots: A Randomized Controlled Trial." *Criminology* 46:577–607.

Brophy, Paul C. and Rhonda N. Smith. 1997. "Mixed-income housing: Factors for success." *Cityscape* 3:3–31.

Bun, Yeng. 2012. "Zillow Rent Index: Methodology."

Burgess, Ernest W. 1925. "The Growth of the City: An Introduction to a Research Project." *Publications of the American Sociological Society* XVIII:85–97.

Buron, Larry F., Susan J. Popkin, Diane K. Levy, Laura E. Harris, and Jill Khadduri. 2002. "The HOPE VI Resident Tracking Study: A Snapshot of the Current Living Situation of Original Residents from Eight Sites." Technical report, U.S. Department of Housing and Urban Development, Washington, D.C.

Byrne, J. Peter. 2003. "Two Cheers for Gentrification." *Howard Law Journal* 46:405–432.

Casciano, Rebecca and Douglas S. Massey. 2012. "Neighborhood Disorder and Anxiety Symptoms: New Evidence from a Quasi-Experimental Study." *Health and Place* 18:180–190.

Charles, C.Z. 2003. "The Dynamics of Racial Residential Segregation." *Annual Review of Sociology* 29:167–207.

Conley, Dalton. 1999. "Getting into the Black: Race, Wealth, and Public Policy." *Political Science Quarterly* 114:595–612.

Connolly, N. D. B. 2014. *A World More Concrete: Real Estate and the Remaking of Jim Crow South Florida*. Chicago: University of Chicago Press.

Crane, Maureen and Anthony M. Warnes. 2000. "Evictions and Prolonged Homelessness." *Housing Studies* 15:757–773.

Crowder, Kyle and Liam Downey. 2010. "Interneighborhood Migration, Race, and Environmental Hazards: Modeling Microlevel Processes of Environmental Inequality." *American Journal of Sociology* 115:1110–1149.

Crowder, Kyle and Scott J. South. 2008. "Spatial Dynamics of White Flight: The Effects of Local and Extralocal Racial Conditions on Neighborhood Out-Migration." *American Sociological Review* 73:792–812.

Curtis, Marah A., Hope Corman, Kelly Noonan, and Nancy E. Reichman. 2013. "Life Shocks and Homelessness." *Demography* 50:2227–2253.

Desmond, Matthew. 2012. "Eviction and the Reproduction of Urban Poverty." *American Journal of Sociology* 118:88–133.

Desmond, Matthew. 2014. "Relational ethnography." *Theory and Society* 43:547–579.

Desmond, Matthew. 2015. "Unaffordable America: Poverty, Housing, and Eviction." *Fast Focus: Institute for Research on Poverty* pp. 1–6.

Desmond, Matthew, Weihua An, Richelle Winkler, and Thomas Ferriss. 2013. "Evicting children." *Social Forces* 92:303–327.

Desmond, Matthew and Monica Bell. 2015. "Housing, Poverty, and the Law." *Annual Review of Law and Social Science* 11:15–35.

Desmond, Matthew and Carl Gershenson. 2016. "Housing and Employment Insecurity Among the Working Poor." *Social Problems* 63:46–67.

Desmond, Matthew and Carl Gershenson. 2017. "Who gets evicted? Assessing individual, neighborhood, and network factors." *Social Science Research* 62:362–377.

Desmond, Matthew, Carl Gershenson, and Barbara Kiviat. 2015. “Forced Relocation and Residential Instability among Urban Renters.” *Social Service Review* 89:227–262.

Desmond, Matthew and Rachel Tolbert Kimbro. 2015. “Eviction’s Fallout: Housing, Hardship, and Health.” *Social Forces* 94:295–324.

Desmond, Matthew and Kristin L. Perkins. 2016. “Housing and Household Instability.” *Urban Affairs Review* 52:421–436.

Desmond, Matthew and Tracey Shollenberger. 2015. “Forced Displacement From Rental Housing: Prevalence and Neighborhood Consequences.” *Demography* 52.

Dwyer, Rachel E. and Lora A. Phillips Lassus. 2015. “The Great Risk Shift and Precarity in the U.S. Housing Market.” *The Annals of the American Academy of Political and Social Science* 660:199–216.

Enterprise Community Partners. 2016. “An Investment in Opportunity: A Bold New Vision for Housing Policy in the U.S.” Technical report.

Formoso, Diana, Rachel N. Weber, and Marc S. Atkins. 2010. “Gentrification and Urban Children’s Well-Being: Tipping the Scales from Problems to Promise.” *American Journal of Community Psychology* 46:395–412.

Fowler, Christopher S. 2016. “Segregation as a multiscalar phenomenon and its implications for neighborhood-scale research: the case of South Seattle 1990 to 2010.” *Urban Geography* 37:1–25.

Freeman, Lance. 2005. “Black Homeownership: The Role of Temporal Changes and Residential Segregation at the End of the 20th Century.” *Social Science Quarterly* 86:403–426.

Freeman, Lance and Frank Braconi. 2004. "Gentrification and Displacement New York City in the 1990s." *Journal of the American Planning Association* 70:39–52.

Friedman, Samantha, Hui shien Tsao, and Cheng Chen. 2013. "Housing Tenure and Residential Segregation in Metropolitan America." *Demography* 50:1477–1498.

Garboden, Philip M.E. and Eva Rosen. 2017. "Contigent Tenure: How Landlords Use the Threat of Eviction." In *The American Sociological Association Annual Meetings*, Montreal, QC.

Gault, Martha and Eric Silver. 2008. "Spuriousness or mediation? Broken windows according to Sampson and Raudenbush (1999)." *Journal of Criminal Justice* 36:240–243.

Gelman, Andrew, Jeffrey Fagan, and Alex Kiss. 2007. "An Analysis of the New York City Police Department's Stop-and-Frisk Policy in the Context of Claims of Racial Bias." *Journal of the American Statistical Association* 102:813–823.

Gelman, Andrew and Jennifer Hill. 2007. *Data Analysis Using Regression and Multilevel/Hierarchical Models*. New York: Cambridge University Press.

Glaeser, Edward and Jacob Vigdor. 2012. "The End of the Segregated Century: Racial Separation in America's Neighborhoods, 1890-2012." Technical report, Manhattan Institute, New York.

Glaeser, Edward L., Joseph Gyourko, and Raven E. Saks. 2006. "Urban Growth and Housing Supply." *Journal of Economic Geography* 6:71–89.

Greenberg, Stephanie W., William M. Rohe, and Jay R. Williams. 1982. "Safe and Secure Neighborhoods: Physical Characteristics and Informal Territorial Control in High and Low Crime Neighborhoods." *National Institute of Justice* 5:141–165.

Guest, Avery M., Charis E. Kubrin, and Jane K. Cover. 2008. "Heterogeneity and Harmony:

Neighbouring Relationships among Whites in Ethnically Diverse Neighbourhoods in Seattle." *Urban Studies* 45:501–526.

Hall, Matthew, Kyle Crowder, and Amy Spring. 2015. "Neighborhood Foreclosures, Racial/Ethnic Transitions, and Residential Segregation." *American Sociological Review* 80:526–549.

Hamilton-Smith, Niall. 2002. "Anticipated Consequences: Developing a Strategy for the Targeted Measurement of Displacement and Diffusion of Benefits." *Crime Prevention Studies* 14:11–52.

Holupka, Scott and Sandra J. Newman. 2012. "The Effects of Homeownership on Children's Outcomes: Real Effects or Self-Selection?" *Real Estate Economics* 40:566–602.

Housing and Urban Development. 2013. "FY 2013 Income Limits Documentation System – Summary for King County, Washington."

Hwang, J. 2015. *The Social Construction of a Gentrifying Neighborhood: Reifying and Redefining Identity and Boundaries in Inequality*, volume 79.

Hwang, Jackelyn and Robert J Sampson. 2014. "Divergent Pathways of Gentrification: Racial Inequality and the Social Order of Renewal in Chicago Neighborhoods." *American Sociological Review* 79:726–751.

Imai, Kosuke and Kabir Khanna. 2016. "Improving Ecological Inference by Predicting Individual Ethnicity from Voter Registration Records." *Political Analysis* 24:263–272.

Kneebone, Elizabeth, Carey Nadeau, and Alan Berube. 2011. "The Re-Emergence of Concentrated Poverty : Metropolitan Trends in the 2000s." *Metropolitan opportunity series* pp. 1–35.

Kreager, Derek A., Christopher J. Lyons, and Zachary R. Hays. 2011. "Urban Revitalization and Seattle Crime, 1982 to 2000." *Social Problems* 58:615–639.

Krysan, Maria, Kyle Crowder, and Michael D. M. Bader. 2015. “Pathways to Residential Segregation.” In *Choosing Homes, Choosing Schools*, edited by Annette Lareau and Kimberly Goyette, chapter 2, pp. 27 – 63. New York: Russell Sage Foundation.

Lee, Barrett A., Sean F. Reardon, Glenn Firebaugh, Chard R. Farrell, Stephen A. Matthews, and David O’Sullivan. 2008. “Beyond the Census Tract: Patterns and Determinants of Racial Segregation at Multiple Geographic Scales.” *American Sociological Review* 73:766–791.

Lees, Loretta, Tom Slater, and Elvin K Wyly. 2007. *Gentrification*. New York: Routledge.

Lichter, Daniel T., Domenico Parisi, and Michael C. Taquino. 2015. “Toward a New Macro-Segregation? Decomposing Segregation within and between Metropolitan Cities and Suburbs.” *American Sociological Review* 80:843–873.

Logan, John and Harvey Molotch. 1987. *Urban fortunes: The Political Economy of Place*. Berkeley: University of California Press.

Maly, Michael T. 2005. *Beyond Segregation: Multiracial and Multiethnic Neighborhoods*. Philadelphia: Temple University Press.

Massey, Douglas S. and Nancy A. Denton. 1993. *American Apartheid: Segregation and the Making of the Underclass*, volume 96. Cambridge, MA.

Massey, Douglas S., Jonathan Rothwell, and Thurston Domina. 2009. “The Changing Bases of Segregation in the United States.” *The ANNALS of the American Academy of Political and Social Science* 626:74–90.

McConnell, Eileen Diaz. 2012. “House Poor in Los Angeles: Examining Patterns of Housing-Induced Poverty by Race, Nativity, and Legal Status.” *Housing Policy Debate* 22:605–631.

McGee, Henry W. Jr. 2007. "Seattle's Central District, 1990-2006: Integration or Displacement." *The Urban Lawyer* 39:167–256.

McKinnish, Terra, Randall Walsh, and T. Kirk White. 2010. "Who gentrifies low-income neighborhoods?" *Journal of Urban Economics* 67:180–193.

Newman, Kathe and Elvin K. Wyly. 2006. "The Right to Stay Put, Revisited: Gentrification and Resistance to Displacement in New York City." *Urban Studies* 43:23–57.

Newman, Sandra J. and C. Scott Holupka. 2014. "Housing affordability and investments in children." *Journal of Housing Economics* 24:89–100.

Oliver, Melvin L. and Thomas M. Shapiro. 2006. *Black Wealth/White Wealth*. New York: Routledge.

Peterson, Ruth D. and Lauren J. Krivo. 2010. *Divergent Social Worlds*. New York: Russell Sage Foundation.

Quillian, Lincoln. 1999. "Migration Patterns and the Growth of High- Poverty Neighborhoods , 1970 1990." *American Journal of Sociology* 105:1–37.

Rugh, Jacob S. and Douglas S. Massey. 2010. "Racial Segregation and the American Foreclosure Crisis." *American sociological review* 75:629–651.

Sampson, Robert J. 2012. *Great American City: Chicago and the Enduring Neighborhood Effect*, volume 53. Chicago: The University of Chicago Press.

Sampson, Robert J., Jeffrey D. Morenoff, and Thomas Gannon-Rowley. 2002. "Assessing "Neighborhood Effects": Social Processes and New Directions in Research." *Annual review of sociology* 28:443–478.

Shapiro, Thomas M. 2004. *The Hidden Cost of Being African American: How Wealth Perpetuates Inequality*. New York: Oxford University Press.

Sharkey, Patrick. 2008. "The Intergenerational Transmission of Context." *American Journal of Sociology* 113:931–969.

Sharkey, Patrick and Jacob W Faber. 2014. "Where, When, Why, and For Whom Do Residential Contexts Matter? Moving Away from the Dichotomous Understanding of Neighborhood Effects." *Annu. Rev. Sociol* 40:559–79.

Shaw, Mary. 2004. "Housing and Public Health." *Annual Review of Public Health* 25:397–418.

Smith, Neil. 1996. *The New Urban Frontier: Gentrification and the Revanchist City*. New York: Taylor & Francis.

South, Scott J and Kyle Crowder. 1997. "Escaping Distressed Neighborhoods: Individual, Community, and Metropolitan Influences." *American Journal of Sociology* 102:1040.

Strahilevitz, Lior J. 2008. "Reputation Nation: Law in an Era of Ubiquitous Personal Information." 102:1–62.

Thomas, Timothy A., Charles C. Lanfear, and Lindsey R. Beach. 2016. "Neighborhood Change & Formal Social Control: Enforcing Racial Social Control through Calls to the Police in Stable & Changing Neighborhoods." In *American Sociological Association Annual Meeting*, Seattle. American Sociological Association.

U.S. Census Bureau. 2017. "American FactFinder - ACS Demographic and Housing Estimates: 2011-2015 American Community Survey 5-year Estimates."

US Census Bureau. 2017. "Maricopa County Added Over 222 People Per Day in 2016." Technical report, US Census Bureau, Washington, D.C.

Wilson, William Julius. 2012. *The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy*. Chicago: University of Chicago Press, 2nd edition.

Wyly, Elvin K. and Daniel J. Hammel. 1999. "Islands of Decay in Seas of Renewal. Housing Policy and the Resurgence of Gentrification." *Housing Policy Debate* 10:711–771.

Wyly, Elvin K. and Daniel J. Hammel. 2004. "Gentrification, segregation, and discrimination in the American urban system." *Environment and Planning A* 36:1215–1241.

Zillow. 2017. "Zillow Data."

Zuk, Mirian, Ariel H. Bierbaum, Karen Chapple, Karolina Gorska, Anastasia Loukaitou-Sideris, Paul Ong, and Trevor Thomas. 2015. "Gentrification, Displacement and the Role of Public Investment: A Literature Review."