Policing Homelessness: Enforcing Neighborhood Change

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Abstract

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US cities have long embraced spatial removal to manage the visibility of homelessness, yet the determinants of these tactics remain understudied. Extant literature often excludes vehicle residents, focuses on formal legal sanctions, and fails to account for the prevalence of homelessness. Addressing such gaps, this study leverages administrative and street outreach data to interrogate the relationship between contemporary removal practices and urban change in Seattle, WA. Spatiotemporal models suggest that increases in neighborhood property value predict more encampment sweeps and vehicle impoundments. Both interventions positively correlate with homelessness-related complaints and crime, while vehicle removals seem further associated with higher concentrations of Black residents and lower population densities. These findings extend prior theories on neoliberal urbanism and social control, suggesting that order maintenance policing may disproportionately target neighborhoods experiencing economic expansion.

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Introduction

On a single night in January 2024, over 770,000 people experienced homelessness in the United States, with approximately 36% sleeping unsheltered (de Sousa and Henry 2024). Cities have historically relied on arrests and trespass ordinances to reduce the visibility of this crisis (Beckett and Herbert 2010). Despite increased investment in non-police alternatives and harm reduction services (Beckett 2023; Collins, Beckett, and Brydolf-Horwitz 2023), many municipalities still actively displace encampments and vehicle residences (Herring 2019; Margier 2023; Pruss and Cheng 2020). Scholarship suggests that these removals worsen people's health, service use, support networks, and criminal legal involvement. Individuals also frequently lose belongings and survival supplies during such events (Chang et al. 2022; Darrah-Okike et al. 2018; Goldshear et al. 2023; Qi et al. 2022). Limited evidence even indicates that encampment sweeps remain ineffective at transitioning people into shelter or housing (Giamarino and Loukaitou-Sideris 2024; Herring, Yarbrough, and Marie Alatorre 2020; Robinson 2019).

Despite these consequences, officials justify clearances as compassionate measures that prioritize public health, community safety, and inhabitant vulnerability, especially when combined with outreach services (City of Seattle 2024b; Margier 2023). However, research on anti-homeless ordinances suggests that spatial removal may instead reflect financial and political pressures to manage urban aesthetics (Collins, Stuart, and Janulis 2022; Kohn 2004; Peck, Theodore, and Brenner 2009), likely to facilitate growth and profit (Beck 2020; Logan and Molotch 1987). Scholars have relatedly demonstrated that complaints from commercial entities and housed residents may prompt such interventions, regardless of safety concerns (Beach 2024; Beckett and Herbert 2010; Herring 2019). Expanding upon such literature, this study investigates the contextual factors that may predict when and where authorities forcibly displace unsheltered individuals.

Scholarship on neighborhood-level determinants of policing homelessness displays several limitations. Prior research largely investigates formal sanctions (e.g., arrests) for quality-of-life offenses, such as disorderly conduct or sit-lie violations. Housed and sheltered individuals could plausibly commit such crimes and thus bias results. Furthermore, scholars often focus on demographic shifts in residential districts. Yet unhoused populations may increasingly sleep in more liminal zones (e.g., industrial areas) partly due to policing practices (Chang et al. 2022; Robinson 2019). Studies also exclude vehicle residents, despite this group exhibiting unique unsheltered experiences (Giamarino, Blumenberg, and Brozen 2024; Pruss 2023). Most notably, literature has not controlled for the prevalence of homelessness, likely due to difficulties with enumerating this issue. Larger outdoor populations could feasibly increase the visibility of targets and thus their exposure to criminal legal contact. Considering this variable will allow us to more confidently isolate the effects of other social and economic conditions.

Addressing these gaps, this paper explores the continued use of spatial removal in political landscapes resistant to harsher legal sanctions – exemplified by Seattle, WA. I specifically leverage administrative data on encampment clearances and vehicle impoundments, which offer improved indicators of unsheltered status. This study also incorporates property value assessments to evaluate a wider array of locations that can experience economic change, including commercial and industrial zones. Lastly, I account for variation in visible homelessness by utilizing case management data on encampment locations. My spatiotemporal models ultimately suggest that sweeps and impoundments correlate with growth in neighborhood property values, even after controlling for homeless prevalence, complaints, and crime. Understanding how these factors affect policing will allow scholars, activists, and officials to more effectively address the criminalization of poverty, as well as potential repercussions of urban change.

Literature Review

Since the late 20th century, cities across the globe have increasingly mobilized the criminal legal system to manage urban aesthetics (Collins et al. 2022; Peck et al. 2009). In the US specifically, jurisdictions responded to rising homelessness in the 1980s by creating civility codes that targeted visible signs of disorder (Blau 1993). In light of the Supreme Court previously invalidating laws that granted police excessive authority to define vagrancy (Papachristou v. Jacksonville 1972), these laws permitted arrest for *specific* offenses, such as sitting or lying on sidewalks (Herbert and Beckett 2010). Municipalities later extended these codes through broader tactics of spatial removal, with Seattle pioneering such actions. Park exclusion ordinances, trespass admonishments, and other orders allowed officials to ban people from public spaces for infractions related to poverty and behavioral health issues (Herbert and Beckett 2010).

This punitive intensification potentially corresponds with sustained pressures of development. Theories of cities as growth machines argue that coalitions of elected officials, landlords, and real estate elites primarily act to raise property values and extract profit from urban landscapes (Beck 2020; Logan and Molotch 1987). Scholarship on neoliberal urbanism similarly attests that municipalities have increasingly commodified space to bolster market-oriented consumption, as well as attract capital and wealthy residents back to disinvested neighborhoods (Collins et al. 2022; Peck et al. 2009). To facilitate these processes, many cities either privatize or exclude non-normative uses from public space, thus bolstering an area's commercial appeal (Kohn 2004; Zukin 2009; Odbert 2022). Tellingly, the National Law Center on Homelessness and Poverty (2017) recently found that 47% of sampled cities banned public sitting or lying, 61% prohibited panhandling, 30% outlawed camping, and 39% proscribed vehicle residency. In Washington State, income disparities even predict the rates of enforcing such laws (Olson, MacDonald, and Rankin 2015).

These neoliberal pressures align with theories of social control that extend beyond the punishment of homelessness. Scholars argue that police serve to not only enforce criminal law but to deter deviant behavior and remove threats to property (Beckett and Herbert 2010; Cahill et al. 2017; Collins et al. 2022). These latter functions have grown pervasive with the popularization of broken windows theory, which associates signs of physical disrepair and social disorder with increased crime (Kelling and Wilson 1982). Perceptions of an inherently criminogenic environment allegedly devalue property and contribute to a spiraling cycle. Local governments have responded by deploying police to expel marginalized populations perceived to jeopardize neighborhood security and value (Collins et al. 2022). In doing so, authorities ontologize not only the environment but also people as criminal (Cahill et al. 2017), namely unhoused and poor residents of color.

Despite their widespread usage, these order maintenance strategies fail to reduce crime or address the underlying conditions that produce poverty. Instead, these methods generate further instability for communities, sever social relationships, and curtail freedoms of both movement and staying in place (Beckett and Herbert 2010; Cahill et al. 2017). As Cahill et al. (2017) contend, sidewalks in targeted neighborhoods become extensions of not only the "prisonized landscape" of carceral power (see Shabazz 2015:2), but also a "privatized landscape" (p. 5). Indeed, these tactics notably occur within or adjacent to neighborhoods experiencing (re)development. In New York City (NYC), for example, researchers have documented positive correlations between police stops and urban change (Beck 2020; Cahill et al. 2017). Drawing on longitudinal census and tax data, Beck (2020) specifically finds that low-level policing intensifies during gentrification and early stages of urban renewal. Between 2009 and 2015, NYC police completed more arrests for quality-of-life offenses and other minor misdemeanors (e.g., trespassing and possession of drugs) following real estate market growth.

In Philadelphia, Smith et al. (2021) similarly demonstrate a positive association between neighborhood change and broken windows policing. Compared to other locations, gentrifying and adjacent tracts experience higher rates of order maintenance arrests and real property forfeitures. Tracts with more vacant property also confront heightened policing. Such strategies moreover appear racialized, disproportionately impacting areas with majority Black and Latinx households. The authors ultimately argue that intensified policing not only follows real estate expansion, but actively primes areas for reinvestment by dispossessing property from and spatially removing minority residents. Such findings echo Cahill et al.'s (2017) remarks that urban development and policing signify intertwined and co-constitutive processes.

People experiencing homelessness represent principal targets of this order maintenance policing. As previously mentioned, Seattle once led the nation in embracing broken windows theory, utilizing arrests and trespass ordinances to banish unhoused and marginalized groups from commercial districts (Beckett and Herbert 2010). Drawing on archival data, Billingham (2017) similarly shows that the city of Wichita, Kansas has repeatedly mobilized law enforcement to displace unsheltered residents from "skid row" in attempts to revitalize downtown. Scholars have further linked these tactics to residential neighborhoods undergoing demographic shifts. Using spatiotemporal methods in Los Angeles, Collins et al. (2022) find that citations targeting homelessness (e.g., sit-lie violations) occur more often in gentrifying tracts characterized by in-migration of wealthier populations and displacement of poor residents. Interestingly, these strategies also target areas undergoing demographic contraction, such as disinvested spaces primed for revitalization. However, the authors do not explore industrial or other liminal zones where people often sleep unsheltered (Chang et al. 2022; Robinson 2019). These studies also do not control for the prevalence of homelessness between areas, which could impact the number of offenses.

Furthermore, law enforcement interactions increasingly do not result in arrests or citations. Past broken windows policing typically involved "aggressive patrol," whereby cities employed legal sanctions to deter low-level criminality and disorder (Herbert, Beckett, and Stuart 2017:1492). Yet in the past decade, many municipalities have adopted slightly less punitive methods to facilitate removal. For example, some law enforcement agencies engage in therapeutic policing (Stuart 2016) or coercive benevolence (Herbert et al. 2017), leveraging threats of arrest to compel individuals into shelter or treatment. Yet in some cases, officers may intervene without channeling people into either the criminal legal system or supportive services. In San Francisco, for example, over 80% of residential and business complaints about homelessness do not result in citation or arrest (Herring et al. 2020). Police instead request people to relocate and stop engaging in law-violating activities. Herring et al. (2020) found that nearly 90% of interviews sleeping outside and 80% of those in vehicles had been displaced by such methods in the past year.

Nevertheless, these non-carceral tactics still likely serve to reduce visible homelessness, rather than help people move indoors. Scholars have repeatedly demonstrated how commercial entities and housed residents pressure public authorities to spatially manage social disorder (Beach 2024; Beckett and Herbert 2010; Herring 2019). Amidst limited resources and growing unsheltered populations, municipalities and police departments increasingly neutralize community complaints by simply shuffling people around public space (Herring 2019). Furthermore, cities have mobilized novel and substantial resources to coordinate these efforts. For example, although police officers participate in the vast majority of move-along orders in San Francisco, these displacements frequently include sanitation workers, security guards, and other public employees (Herring et al. 2020). For nearly a decade, the City of Seattle has similarly coordinated million-dollar budgets across multiple agencies to hide homelessness (Kim Jr and Oron 2020; Oron 2024a).

Tellingly, these practices harm unsheltered individuals by dispossessing property, creating barriers to services, and increasing vulnerability to crime. Although often occurring without criminal sanctions, this policing can involve civil penalties, which can burden recipients with court debt, suspended licenses, poor credit, and bench warrants (Herring et al. 2020). These impacts can jeopardize employment and rental prospects, as well as disqualify people from housing programs (Herring et al. 2020). Such consequences seem especially pronounced for vehicle residents, as cities respond to surges in this population with tickets and parking restrictions (Pruss and Cheng 2020). In 2017, for example, Seattle issued over 1,100 vehicle residency-oriented parking tickets, with around 60% of initial penalties going unpaid. These fines can result in impoundment and even street homelessness. Despite vehicle residents comprising over half of King County's unsheltered community in 2018, this issue nevertheless remains understudied (Pruss and Cheng 2020).

However, during the COVID-19 pandemic and Black Lives Matter protests, cities across the US either paused or substantially slowed practices of spatial removal. In addition to tolerating encampments per public health guidelines, many municipalities expanded low-barrier shelters, non-police crisis teams, Housing First programs, and other harm reduction services (Beckett 2023; Colburn et al. 2022; Collins et al. 2023). Collins et al. (2023) emphasize the need to investigate such countervailing trends, proposing that scholarship centering theoretically deviant cases can reveal contradictions and opportunities for change within neoliberal poverty management. They explore a project pioneered in 2020 by Seattle's Public Defender Association, which utilized hotels to shelter people, provide social services, and reduce criminal legal involvement. Interestingly, representatives from the Downtown Seattle Association (funded by the Metropolitan Improvement District), Chamber of Commerce, and business community eventually embraced the initiative "as a revolutionary path forward" for addressing homelessness (Collins et al. 2023:196).

Echoing Peck et al. (2009), I nonetheless believe that these fluctuations should encourage scholars to recognize "the contextual embeddedness and path dependency" of neoliberal projects (pp. 49-50). "[A]ctually existing neoliberalism" can generate internal inconsistencies, such as reformative policy responses, given that authorities must intervene in the consequences of market failures (Peck et al. 2009:49). Governance strategies also prove geographically variable and non-linear, considering that cities confront distinct policy environments, spatial landscapes, and public resistance (Peck et al. 2009). Accordingly, interventions that clear the streets by transitioning people indoors could coexist with exclusionary financial interests, particularly in more progressive cities experiencing commercial and real estate growth (e.g., Seattle). Communities must continue interrogating the predictors and motivations behind such shifts, which may obscure inequitable underlying processes.

Moreover, the expansion of supportive programs may represent a temporary anomaly caused by extraordinary circumstances. Collins et al. (2023) importantly note that cities experienced post-pandemic demands for punitive policing as business districts reopened. This resurgence has particularly manifested in liberal cities in the form of encampment clearances (Cline 2022). The Department of Housing and Urban Development (HUD) describes encampments as temporary structures or enclosed places not intended for long-term habitancy, which people occupy on a continuous basis (Cohen, Yetvin, and Khadduri 2019; Dunton et al. 2020). Seattle's Finance and Administrative Services (FAS) Rule 17-01 (2017) similarly identifies encampments as "one or more tent[s], structure[s], or assembl[ies] of camping equipment or personal property" in active use, including vehicles. In addition to these material aspects, literature also includes unsheltered residents within definitions (APHA 2023).

The number of encampments has grown rapidly since the Great Recession, now present across all US states (NLCHP 2017). Yet despite this widespread prevalence, encampments differ considerably across jurisdictions in terms of scale and legal status. Some cities have passed legislation permitting them on public property, with varying degrees of regulations. For example, Seattle allows a few sanctioned sites, for which the city facilitates access to property and services (Junejo 2016). Additionally, the First Amendment and occasionally local laws often protect religious groups from ordinances prohibiting encampments on private property. Washington State explicitly permits religious organizations to host sites, with limited interference from local jurisdictions (Junejo 2016). This study nevertheless focuses on unauthorized encampments in public spaces, which often face heightened risks of policing and removal. According to the National Coalition for the Homeless, at least 65 US cities criminalized or cleared such encampments as of early 2022 (Cline 2022).

Among locations with prohibitive laws, encampment sweeps typically involve evicting inhabitants, removing personal property, and disbanding structures (APHA 2023; Chang et al. 2022). Authorities might further install signage and "hostile architecture" (such as fencing) to deter future occupancy (Kim Jr and Oron 2020). Vehicle residents may additionally receive parking tickets and traffic violations, as well as face towing and impoundment (Pruss and Cheng 2020). Refusing to relocate can also result in arrest, criminal summons, civil citations, and confiscation of belongings (Chang et al. 2022; Robinson 2019). Though authorities often conduct sweeps in adherence to local ordinances, cities may initiate them due to neighbor complaints, as well as environmental, sanitation, and crime concerns (Beach 2024; Chang et al. 2022). Other terms for this practice include removals, clearances, abatements, and raids.

The Seattle Mayor's Office notably refers to these tactics as "resolutions" (City of Seattle 2024b), reflecting stated goals of improving public safety and connecting people with resources. Cities have embraced such rhetoric to increasingly mobilize non-police actors during sweeps, namely outreach workers. Exploring clearances in Portland, OR, Margier (2023) however cautions that these supportive services may inadvertently facilitate spatial removal. Although expanding supportive services, the city's outreach strategies primarily target the most noticeable encampments for closure. This "compassionate invisibilization" allows Portland to appease both advocates opposing arrest and residents complaining about disorder (Margier 2023:193). Herring (2021) observes similar processes in San Francisco, whereby authorities weaponize shelter expansion to justify clearing encampments, despite limited bed capacity and degraded conditions. These interventions thus still legitimize the spatial removal of unsheltered individuals and destruction of their residences. Although benevolent notions of harm reduction underlie official discourse, practices of care and punishment appear increasingly intertwined in the management of homelessness.

Nevertheless, this practice has sustained much legal scrutiny for violating the Fourth, Eighth, and Fourteenth Amendments for unreasonable seizure, cruel and unusual punishment, and unequal protections (Lavan v. Los Angeles 2012; Ellis v. Clark County 2016; Coalition on Homelessness v. San Francisco 2022; Kitcheon v. Seattle 2023). However, the US Supreme Court recently determined that enforcing public camping bans does not violate the Eighth Amendment (Grants Pass v. Johnson 2024), thus allowing cities to issue criminal and civil penalties for sleeping unsheltered. Regardless of constitutionality, sweeps do not appear associated with compassionate outcomes. Clearances can occur unpredictably and without warning, causing absent residents to lose possessions (Goldshear et al. 2023). For those present, removals can still result in the destruction of belongings and survival supplies (Chang et al. 2022; Darrah-Okike et al. 2018).

Additionally, sweeps may worsen physical well-being by decreasing security, disrupting healthcare access, and interfering with disease management (Chang et al. 2022; Chiang et al. 2022; Qi et al. 2022). Clearances can also negatively impact mental health and social connections (Darrah-Okike et al. 2018; Goldshear et al. 2023). Furthermore, removals can involve adversarial encounters with law enforcement, causing residents to avoid contacting police in the future (Chang et al. 2022). Limited evidence even suggests that sweeps do not effectively bring people indoors (Giamarino and Loukaitou-Sideris 2024; Hayes-Chaffe 2023; Herring et al. 2020; Roy et al. 2022). They may instead simply reduce the visibility of encampments by repetitively displacing people (Darrah-Okike et al. 2018; Goldshear et al. 2023; Herring et al. 2020) or forcing them into isolated environments (Chang et al. 2022; Robinson 2019). This study ultimately evaluates whether economic and social pressures inform these practices of managing urban aesthetics.

Study Site

Seattle provides a unique site to examine whether these non-penal interventions reflect neoliberal growth and development. King County, WA claims the fourth highest homelessness count among major metropolitan areas, following New York City, Los Angeles, and Chicago (HUD 2024).[1] On a given night in January 2024, more than 16,000 people experienced homelessness in the area, with 60% sleeping unsheltered (KCRHA 2024). In Seattle and elsewhere, the combination of high population growth, extreme housing costs, and low supply elasticity has likely facilitated marked rises in homelessness in the past decade (Colburn and Aldern 2022). Alongside rapid development, this economic expansion has also contributed to gentrification and displacement of minority residents (Fogal 2020; Hwang 2020).

[1] This county-city comparison has received criticism, given that rates of homelessness are often higher in urban than suburban areas (Colburn and Aldern 2022). County counts may thus underestimate the scale of this issue in Seattle.

Additionally, Seattle has long embraced order maintenance policing to manage the visibility of disorder. The city notably adopted a parks exclusion law in 1997, permitting police and public officials to ban people from these spaces for minor infractions (e.g., remaining after hours and camping) (Beckett and Herbert 2010). This authority thereafter expanded to cover other places, including libraries, recreation centers, transit systems, universities, hospitals, and social services. These interventions and, to a lesser extent, trespass admonishments disproportionately occurred in downtown commercial districts. However, Stay Out of Drug Area (SODA) and Areas of Prostitution (SOAP) orders also banned individuals convicted of related offenses from wider swaths of the city (Beckett and Herbert 2010).

Violations of such orders often resulted in criminal charges that only exacerbated barriers to employment and housing (Beckett and Herbert 2010). Spatial banishment also complicated people's access to vital material, social, and emotional resources, rendering compliance largely impossible (Herbert and Beckett 2010). Instead of reducing targeted behaviors, these practices simply lowered probable cause for arrest, leading the city to eventually abandon some policies in 2010. Yet encampment clearances and vehicle impoundments have nevertheless extended the broken windows logic of these tactics, constituting a key component of municipal policy over the past two decades. In 2005, King County's 10-year plan to end homelessness first developed guidelines for clearing unauthorized encampments (CEHKC 2005).[2] Media analyses during this period suggest that the city justified removals as necessary for public health and safety, relying on rhetoric of filth and contagion (Bawarshi et al. 2008). Narratives moreover emphasized perspectives of homeowners, suggesting preoccupations primarily with the impacts of visible disorder.

[2] These guidelines followed a decree that sanctioned some regulated tent cities as an emergency response to the lack of shelter (CACHE 2004). Following protest, the City Council passed legislation in 2011 legalizing encampments on church property. In 2015, the municipality allowed temporary tent cities elsewhere (Seattle Municipal Archives 2024).

By 2015, Mayor Ed Murray declared a Civil Emergency against homelessness, dedicating a third of over $7 million to clearing encampments (Murray 2015). Media and displaced residents described the ensuing sweeps as disorganized, with limited outreach, frequent seizure of belongings, and inadequate housing resources (Baker 2016; Cawthon 2016). Within two years, the city created the Navigation Team (NT) to formally coordinate clearances between various agencies. The entity's budget eventually exceeded $8 million by 2020, with a substantial portion of members drawn from the Seattle Police Department (Kim Jr and Oron 2020). Per public records, the NT displaced over 900 encampments in 2019 alone (Figure 1), with a peak of 120 removals in August. However, the COVID-19 pandemic soon granted temporary reprieve, with the city disbanding the NT and pausing nearly all clearances due to public health concerns (Kim Jr and Oron 2020; Oron 2024a). Accordingly, records document 90 removals from April 2020 through December 2021, representing a substantial decrease from prior years (Figure 1).

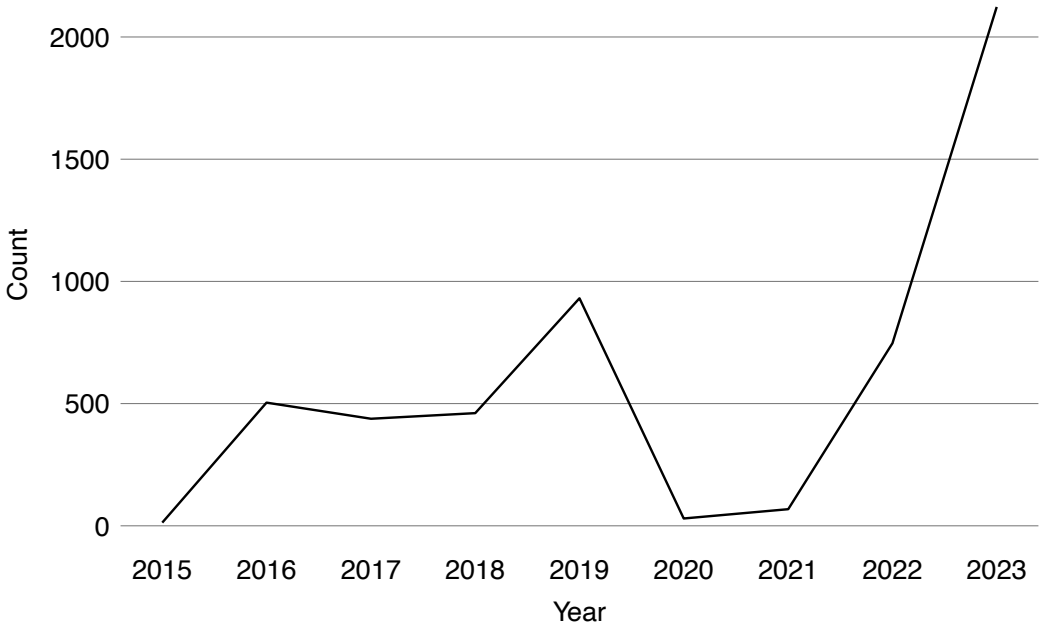

Figure 1. *Annual numbers of encampment clearances in Seattle, WA.*

Yet this relief quickly ended as Mayor Bruce Harrell began campaigning on addressing highly visible homelessness (Cline 2022). By May 2022, Harrell released the *One Seattle Homeless Action Plan*, espousing that encampments prove unsafe for inhabitants and communities (City of Seattle 2024b). The administration then established the Unified Care Team (UCT) to coordinate municipal departments and partner organizations in "resolving" sites. The program operated a $26.6 million budget in 2024, with $2.2 million for police wages and $1.7 million for outreach staff (Oron 2024b). Following trends in other west coast cities (Margier 2023), the UCT significantly revamped displacement practices, clearing at least 2123 sites in 2023 and 921 through May 2024. Although prioritization of removals allegedly depends on health and safety risks (e.g., mobility impacts, chemical hazards, crime history), I interrogate other neighborhood-level determinants that might influence these interventions.

Methods

Data

To evaluate predictors of policing homelessness, this study employs administrative data from the City of Seattle, King County, and a non-profit service provider. Information on encampment clearances was obtained under the Freedom of Information Act via public records requests to the Mayor's Office and UCT. The compiled dataset lists the dates and locations of sweeps conducted by the city between 2015 and 2023. I similarly procured data from the Seattle Police Department (SPD) and Department of Finance and Administrative Services (FAS) on public impoundments from 2014 through 2023. These files include towing dates, addresses, and coordinate locations, as well as vehicle types and reasons for removal.

Measures of neighborhood change incorporate annual land and improvement values of tax parcels between 2013 and 2023 from the King County Assessor (2024). With respect to controls, my models leverage crime records from Seattle's Open Data Portal (2024c). I also acquired data on requests (i.e., "complaints") submitted to the Customer Service Bureau (CSB) regarding unauthorized encampments, vehicle residences, 72-hour parking violations, and illegal dumping of needles. Variables reflecting population density and racial composition come from American Community Survey (ACS) five-year tract estimates (US Census Bureau 2024). Finally, I control for encampment prevalence with data from Evergreen Treatment Services (ETS) REACH, a local homeless service provider. This study summarizes all variables at yearly and neighborhood levels based on Community Reporting Areas (CRAs) (see appendix Figure A1 for a reference map).[3]

Measures

Literature varies significantly in operationalizing key variables, largely depending on the target population. For example, Collins et al. (2022) examine interventions against homelessness by using charges that potentially reflect housing status (e.g., sit-lie citations). Conversely, Smith et al. (2021) investigate gentrification more broadly, allowing them to incorporate other misdemeanors and property forfeiture. For this study, I specifically focus on unsheltered residents by assessing encampment clearances and vehicle impoundments. Reflecting broken windows policing, these tactics involve both spatial removal and property dispossession. Yet they also indicate homelessness more accurately than prior measures, which assume living situation based on behaviors rather than nighttime residence. Compared to sleeping elsewhere (e.g., on benches), tents and vehicles also present more visible and sustained barriers to the commodification of space.

[3] CRAs align with census tract boundaries, permitting seamless linkage with demographic data. The city also reviewed existing neighborhood geographies to create these areas (City of Seattle 2024a).

Encampment interventions can assume a variety of forms. Between 2017 and 2021, for instance, public records distinguish between inspections, litter picks,[4] advanced notice removals, and sweeps due to hazards or obstructions. I only include events that formally clear residents and structures. Given inconsistent recordkeeping, observations prior to 2022 also do not always include coordinate information. Therefore, I first fill missing values by matching location names. For other observations, I standardize location text due to non-uniform entry of addresses, intersections, and sites. I thereafter use the *tidygeocoder* package to provide coordinates (Cambon et al. 2021).[5] Finally, I deduplicate sweeps within 200 feet of each other (1.3% of the remaining sample), which reflects distances cited elsewhere to identify encampments based on tent clusters (Finnigan 2021). This results in a final dataset of 5315 sweeps from January 2015 through December 2023.

With respect to vehicle removals, I combine FAS and SPD data on impoundments occurring on rights-of-way and other publicly owned or controlled property (e.g., parking lots). I then subset violations that disproportionately affect or indicate unsheltered status (Table 1), as documented elsewhere (Pruss 2023; Pruss and Cheng 2020).[6] My analysis incorporates vehicle types typically used as shelter, including sedans, hatchbacks, station wagons, SUVs, trucks, vans, buses, and recreational vehicles (RVs) (Pruss 2023). Given the high incidence and potential noise for 72-hour infractions, I only include RVs for this offense. Keeping all styles for the other violations helps capture different unsheltered experiences and avoids biasing locations where oversized vehicles often park. Lastly, I fill any missing coordinates and deduplicate removals that share dates,

[4] Based on publicly available encampment journals, the city inspected and removed litter at some sites without pursuing further action – a tactic that scholars have observed in other US cities (Goldshear et al. 2023).
[5] I use the Coordinate Reference System (CRS) projection EPSG:4269 for *tidygeocoder.* Thereafter, I employ the NAD83 (EPSG:6596) metric projection appropriate for Seattle (U.S. National Geodetic Survey 2022).
[6] Unlike Pruss (2023; 2020), I do not include code 11.72.070, which prohibits oversized vehicles from parking overnight in certain non-industrial areas. My data contains few examples (all prior to August 2021), many of which involve flat-beds and tractor trailers. Additionally, I do not want to bias certain zoning types or neighborhoods.

Table 1. *Infractions Related to Impounded Vehicle Residences.*

Violation	Municipal Code	Description
72-Hours	11.72.440	Restricts parking to 72-hours max
Junk	11.72.500	Prohibits inoperable vehicles
Detached	11.72.430	Forbids detached trailers or campers
Scofflaw	11.35.010-040	Targets owners with multiple unpaid tickets
Public Park	18.12.235	Bans vehicles in public parks after hours

Note: Per SPD, vehicles in violation of 11.72.440 are commonly referred to as "abandoned."

vehicle types, codes, and locations within 30 feet (4.9% of the remaining data).[7] The final sample consists of 9716 impoundments from January 2014 through December 2023. Similar to encampments, the city displaced fewer vehicle residences during COVID-19. Seattle paused the 72-hour parking rule in March 2020, began clearing abandoned and hazardous vehicles again in October 2021, and resumed full enforcement in May 2022 (Figure 2).

[7] Non-uniform entry of addresses (e.g., not including "St" or "Ave") can result in slight coordinate differences between the FAS and SPD data. Thirty feet reasonably buffers for distances across intersections and two-lane streets.

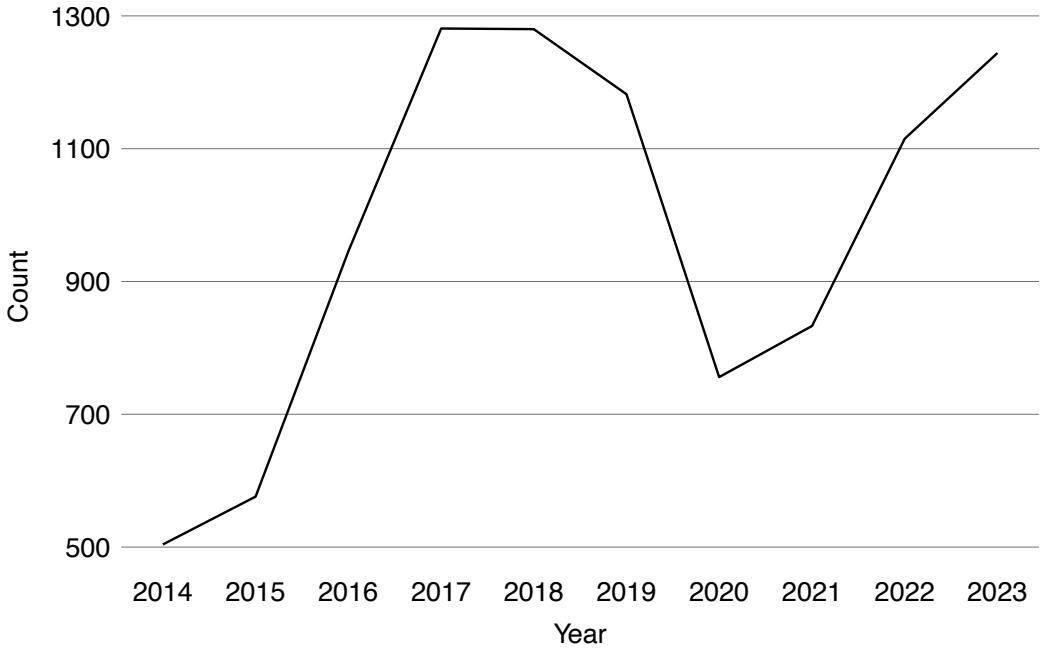

Figure 2. *Annual numbers of vehicle residence impoundments in Seattle, WA.*

Order maintenance scholars often operationalize neighborhood change based on demographic shifts in median income, home prices, rent, education levels, and racial composition (Collins et al. 2022; Smith et al. 2021). Although accounting for population attributes, this study instead focuses on economic expansion in terms of property values – a measure previously applied by Beck (2020) to examine development-oriented policing and gentrification in New York City. I specifically match tax parcels (including non-improved ones) to CRAs and calculate a total property value for the neighborhood. For each year, I then compute the percent change in value from the prior period as a continuous variable. Although this approach may limit theorizing about demographic shifts, property assessments aptly suit frameworks of neoliberal urbanism and growth. This indicator also permits modelling change in less residential spaces (i.e., industrial zones), which scholars often exclude from analyses due to limited demographic data. Researchers must find methods to evaluate policing in these liminal areas where people often sleep unsheltered.

With respect to controls, prior studies have not accounted for the prevalence of homelessness when claiming that policing correlates with gentrification (Collins et al. 2022; Goldfischer 2020). More people sleeping outside could increase exposure to residential complaints and law enforcement contact, potentially amplifying citations, arrests, and other interventions. As a proxy for visible homelessness, I therefore leverage data on encampment locations from ETS REACH, the largest homeless services contractor to King County's public health department. Another research team (Sutton et al. 2025) already validated 742 sites encountered by outreach workers between February 2016 and September 2022. Although the data includes date ranges for when staff observed a location, sites could exist before and after these periods, as well as become inactive between visits. As such, I simply categorize areas as having constantly low, medium-low, medium-high, or high level of encampments based on quartile distributions (Figure 3).

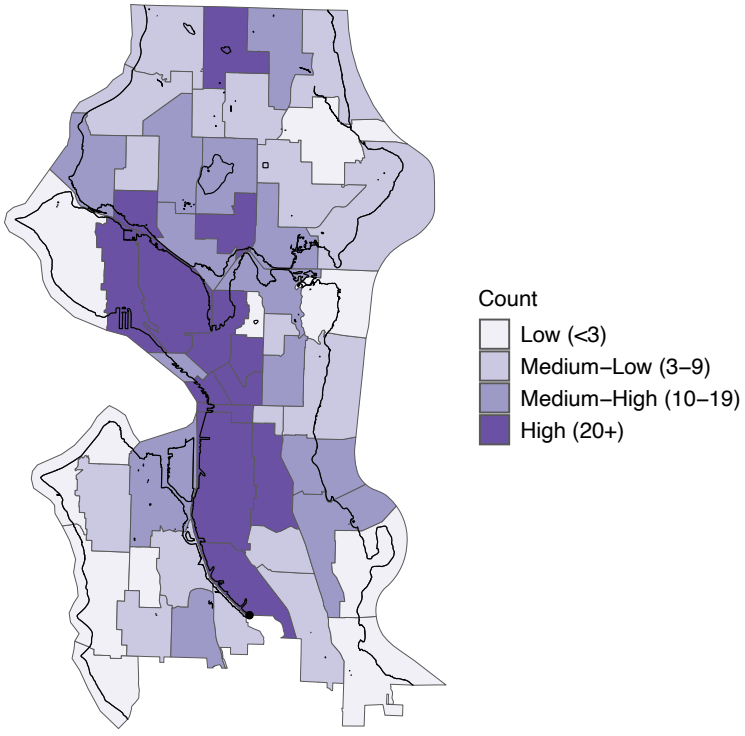

Figure 3. *Prevalence of encampments encountered by ETS Reach (2016-2022).*

Given that policing trends could reflect complaint patterns (Herring 2019), I also adjust for homelessness-related customer service requests. In 2013, the City of Seattle developed the *Find It, Fix It* (FIFI) phone application for people to report minor problems (e.g., potholes, parking violations). Although initially omitting categories related to homelessness, users could submit requests under "General Inquiry," which CSB staff flagged with labels like unauthorized camping. Beach (2024) notes that FIFI usage grew slowly, and that the app only began including specific options for homelessness in 2018. Although this delayed uptake and initial lack of encampment categories could bias effects, I control for complaints across the entire time period. I specifically model the yearly count of requests related to unauthorized encampments, 72-hour (i.e., "abandoned") parking, and illegal dumping of needles (due to common associations with homelessness per Beach (2024)).[8] Such complaints have steadily increased over the past decade, dipping briefly during the pandemic before surging to over 115,000 requests in 2023 alone (Figure 4).

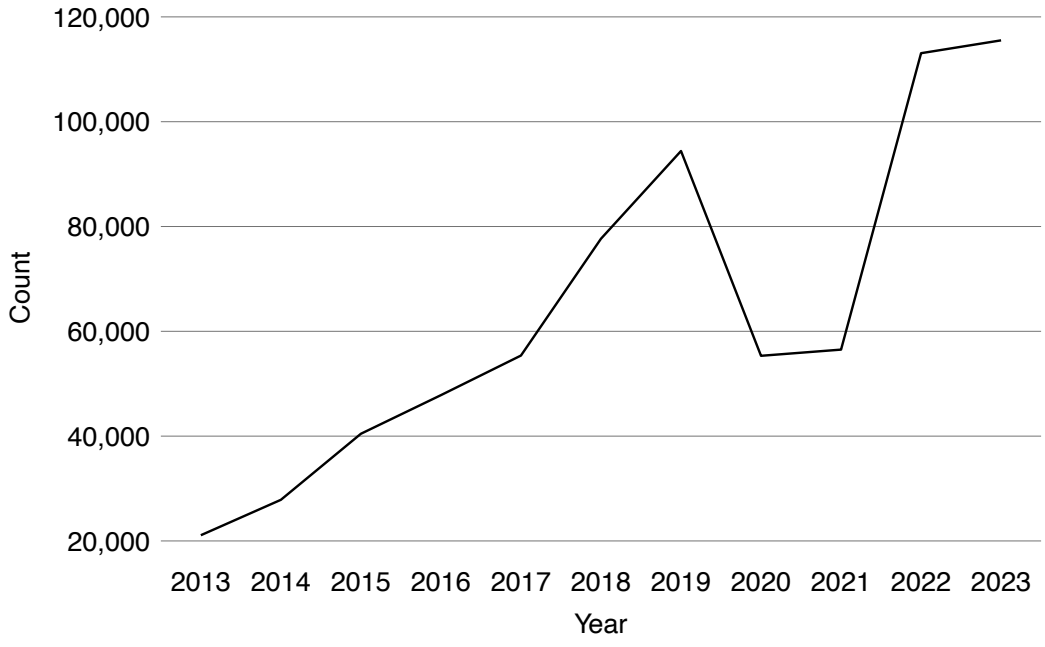

Figure 4. *Annual numbers of homelessness-related complaints in Seattle, WA.*

[8] This data also contains complaints submitted directly via the Customer Service Requests portal.

Analysis

To examine the relationship between urban change and policing homelessness, this study employs various spatial and temporal methods.[9] I first conduct tests for autocorrelation in each neighborhood's time series for all outcome variables. I then assess overdispersion and spatial dependencies with Generalized Linear Models (GLMs). Based on these results, I fit conditional autoregressive (CAR) Besag-York-Mollié 2 (BYM2) models using integrated nested Laplace approximation (INLA). These techniques account for correlation between years and neighboring CRAs, allowing me to more accurately isolate the effects of my explanatory variables. For example, a Negative Binomial CAR BYM2 autoregressive model assumes the following general form:

$$Y_t \sim NegBin(\mu_t, \theta) \tag{1}$$

where Y_t represents an area's count of removals (e.g., clearances) in year *t*, modeled with a mean of μ_t and dispersion parameter θ. A log link function then summarizes μ_t as:

$$\mu_t = \beta_0 + \beta_i \boldsymbol{X_i} + \rho y_{t-j} + \psi_{it} + \varepsilon_i \tag{2}$$

where β_0 represents a latent intercept; β_i signifies the vector of regression coefficients; X_i indicates the corresponding covariates; ρ is the temporal autoregressive parameter for j^{th} lags (i.e., j = for AR(1)); and ε_i represents an independent error term. Lastly, the random effects parameter ψ_{it} under INLA assumes:

$$\psi_{it} = \psi_i + \delta_t, i = 1, \dots, n, t = 1, \dots, T, \tag{3}$$

$$\psi \sim \text{CAR}(\phi|W, 1, \tau^2),$$

$$\delta_t \sim N\left(\rho_T \delta_{t-j}, \tau^2\right),$$

$$\delta_0 \sim N(0, \tau^2)$$

[9] See appendix for a complete description of time series diagnoses (e.g., ACF, PACF, and Ljung-Box) and spatial tests (e.g., Moran's I).

where ψ represents the vector of spatial random effects for n areas, with a dependence parameter ϕ given a contiguity-based spatial adjacency matrix W; δ_t signifies the temporal random effect for each period based on the j^{th} lag; and δ_0 is the remaining unstructured noise (Sahu 2022). All models employ penalized complexity priors, which provide more conservative regression estimates and help avoid overfitting by shrinking parameters toward simpler null structures (e.g., zero variance). I perform analyses in *R* (v 4.4.3; R Core Team 2025) with the *bmstdr* (Sahu, Lee, and Bakar 2023) and *simcf* (Adolph 2024) packages.

Results

The policing of homelessness does not appear evenly distributed among Seattle neighborhoods, suggesting an unequal burden in law enforcement exposure. The median number of sweeps across Community Reporting Areas (CRAs) rarely reaches 10 a year (Figure 5). Yet maximum counts exceed 50 in most periods, with some locations documenting over 200 sweeps in 2019 and 2023. Impoundments also seem concentrated in certain neighborhoods, despite displaying less spatial variation than sweeps. While the median number of vehicle removals never surpasses 20, the maximum count often reaches 80 and even exceeds 100 in multiple years, including during the COVID-19 pandemic (Figure 6). Although these descriptions mask area-specific trends, mapping total counts across the entire time frame also reveals substantial neighborhood differences (Figure 7). Both interventions show similar patterns, though sweeps especially predominate in Downtown and Ballard (northwest). Impoundments particularly affect southern (e.g., SODO, Georgetown) and southeastern areas (e.g., Rainier Beach, Colombia City), as well as the Lake Washington Ship Canal. These trends partly resemble that of encampment prevalence (Figure 3), highlighting the importance of controlling for this variable in further analyses.

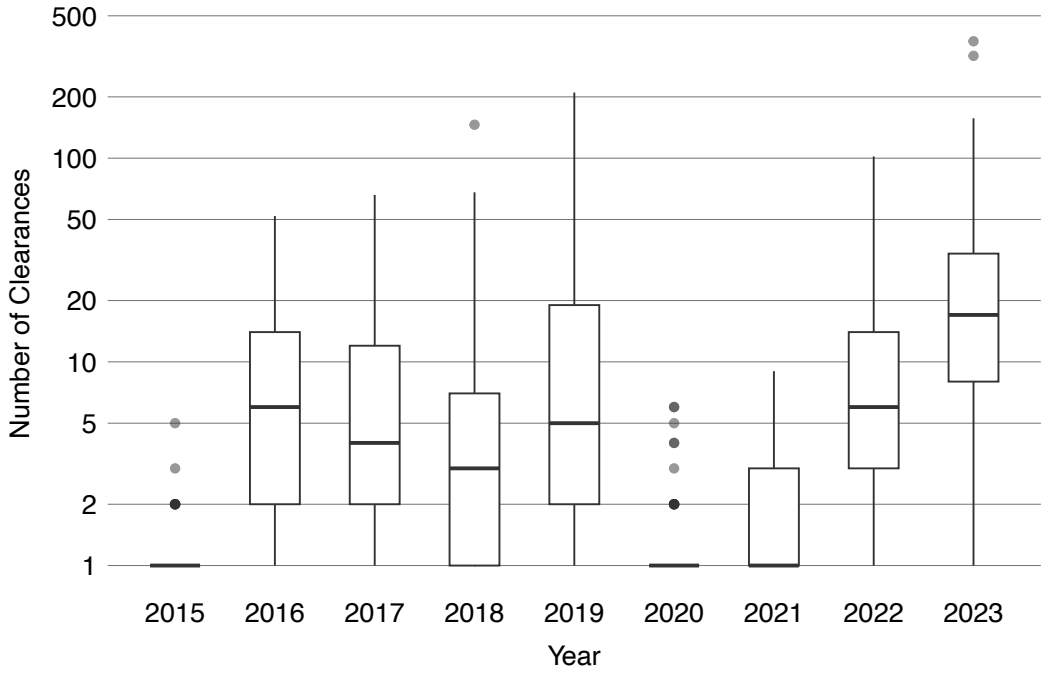

Figure 5. *Yearly distribution of encampment clearances across CRAs.* All areas receive an offset of 1 to account for zero counts. Horizontal lines in boxes represent median values, while dots signify outliers (below or above 1.5 times the interquartile range).

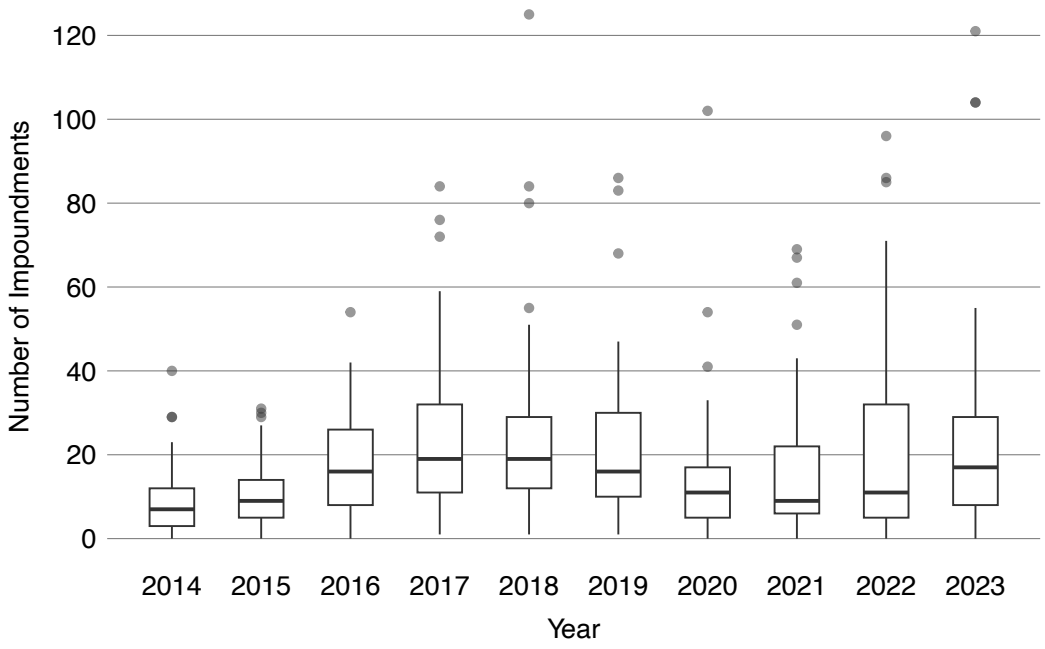

Figure 6. *Yearly distribution of impoundments across CRAs.*

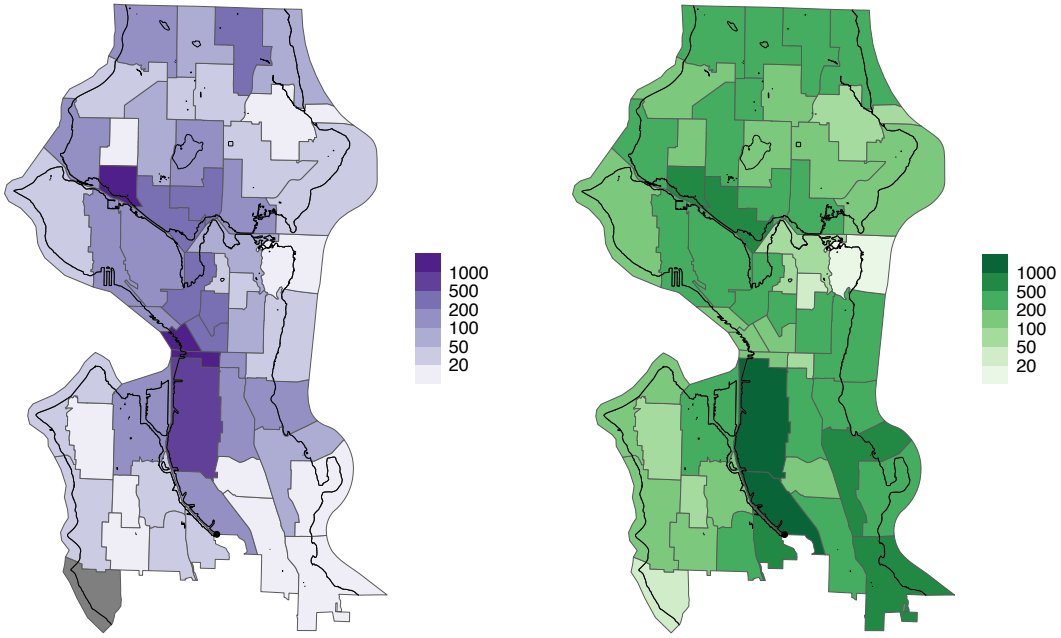

Figure 7. *Total counts of clearances (left, 2015-2023) and impoundments (right, 2014-2023).* Grey indicates no removals.

Again, I wish to interrogate how the temporal and spatial distribution of policing relates to broader social and economic conditions. Seattle has experienced marked and widespread growth in the past decade, with the median CRA gaining property value every year (Figure 8). Nevertheless, neighborhoods still exhibit variation in their levels of expansion. For example, approximately one quarter of CRAs lost value in 2018 and 2021, with some non-outliers also showing declines in 2020 and 2022. Although total values increased for all neighborhoods across the study period, downtown neighborhoods experienced the most composite growth, with Cascade, East Lake, and South Lake Union rising by nearly 300%. Locations around Ballard, Capitol Hill, and Columbia City also tripled in value. The industrial districts of SODO and Georgetown witnessed less expansion (81% and 112%, respectively), yet their change mirrored that of already wealthy locations in north and east Seattle (e.g., Laurelhurst, Montlake, and North Capitol Hill). I will leverage such differences to assess the relationship between spatial removal and economic change.

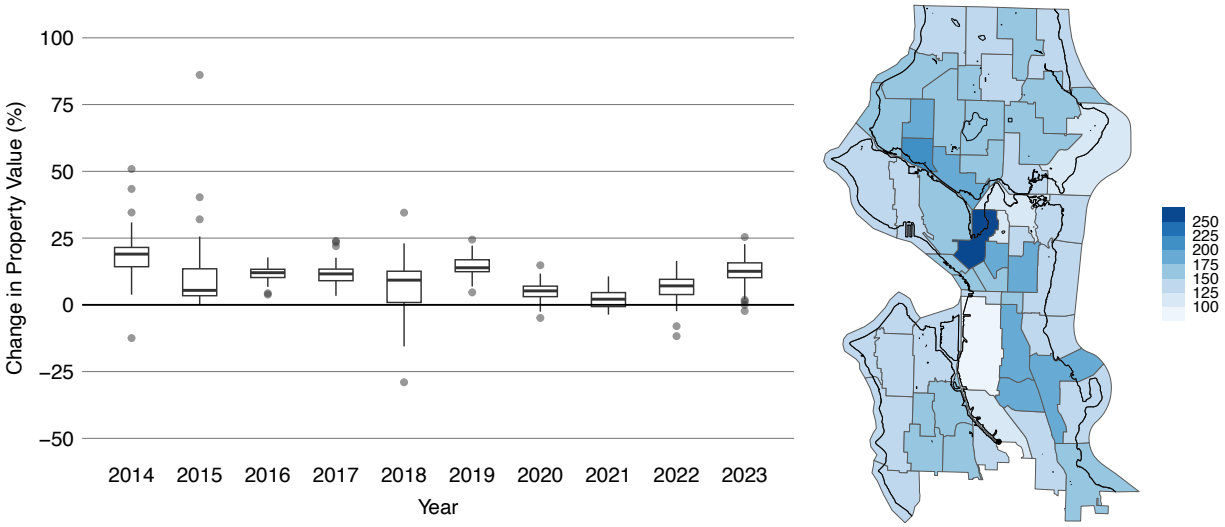

Figure 8. *Distribution of CRAs by yearly (left) and total percent shifts in property value (right, 2013-2023).*

Isolating the effects of neighborhood conditions first requires interrogating whether time and geography influence policing trends. Despite large ranges in total removal events, I find little evidence of temporal correlation in their yearly values. Across nearly all neighborhoods, annual numbers of sweeps and impoundments do not appear associated with those of prior periods. For example, the previous year's count does not predict increased or decreased events in the current one. The volatile political climate around homelessness and policing likely produced wide fluctuations in clearance tactics throughout the period. Seattle also paused most sweeps and 72-hour parking impoundments during the COVID-19 pandemic. As a result, autocorrelation tests might not discern any significant relationships between counts over time. Nevertheless, Moran's I tests suggest significant associations in removal practices between adjacent CRAs ($p < 0.001$). In a given year, interventions in one location can help predict those in adjoining neighborhoods. Such patterns could reflect a spillover effect due to sweeps pushing people into nearby areas or police expanding their patrol zones.

CAR BYM2 models allow us to incorporate this information from neighboring CRAs to better estimate removal counts. By adjusting for spatial dependencies, they can more accurately specify relationships between variables. Given that complex time patterns could still exist in the data despite our diagnostic findings, I also test temporal parameters in several models.[10] For sweeps, a Negative Binomial (NB) distribution most accurately fits the observed data, as expected given overdispersion in exploratory Poisson GLMs ($p < 0.001$). First order autoregressive AR(1) and random walk RW(1) models display the best in-sample fit, yet a non-autoregressive AR(0) formulation performs comparably out of sample (Table A1). I prefer the simpler non-temporal model, given the lack of strong empirical evidence and theoretical arguments for serial correlation.

Using this NB AR(0) model, I estimate the relationships between contextual factors and a CRA's annual count of encampment clearances (Figure 9, see Table A3 for rate ratios). Net of other parameters, a percentage point gain in property value between years correlates with a 4.6% increase in the predicted number of sweeps (95% CI 2.6 to 6.7).[11] Controlling for other variables, an additional 100 homelessness-related CSB requests raises the estimated count by 8.1% (95% CI 6.2 to 10.1); and a percentage point increase in crime rates drives up sweeps by 139.3% (95% CI 51.5 to 265.4). Each of these changes is statistically significant ($p < 0.05$). Clearances also appear positively associated with population density at an alpha level of 0.1. However, the concentration of Black residents seems consistent with a null effect.[12] Interestingly, encampment prevalence does not appear predictive of sweeps, and excluding this variable results in comparable model fit (DIC 2267 versus 2269; RMSE 20.0 versus 19.7). As such, enforcing anti-camping ordinances may depend less upon the prevalence of offenders than on other neighborhood characteristics.

[10] The appendix provides model comparisons, including in-sample fit, cross validation, and regression results.
[11] Using total yearly value instead of change in value results in a non-significant association (Table A5).
[12] Modeling the percentage of White residents does not shift the sign nor significance of this relationship (Table A6).

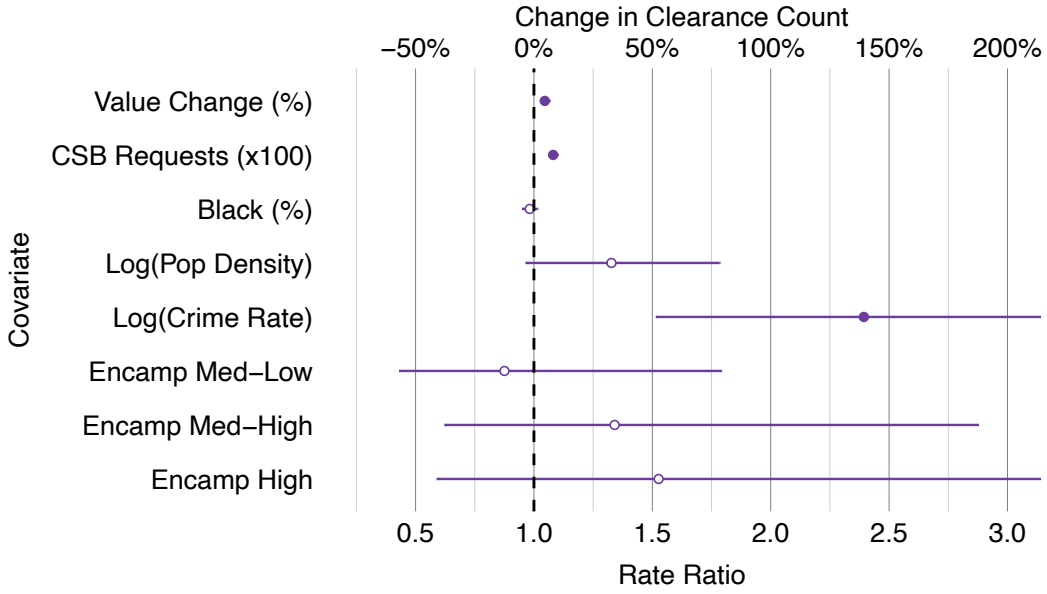

Figure 9. *Posterior medians and 95% credible intervals for sweeps CAR model.* Filled circles suggest statistical significance. Low encampment prevalence serves as the reference.

With respect to vehicle removals, choice criteria similarly indicate that Negative Binomial distributions best correspond to the data, with AR(1) and RW(1) models attaining the greatest fits (Table A2). In contrast to clearances, the non-temporal model does not perform as well in cross validation. Although previous tests suggest no autoregression in the demeaned and detrended time series, a random walk may account for other complex patterns in the observed data. For example, counts of impoundments could reflect those of the prior year, with variations introduced gradually over time. In contrast to sweeps, which may respond to short-lived political shifts, vehicle removals might instead correlate with more stable factors, such as population density or traffic law enforcement. This could generate a process characterized by longer-term dependence rather than volatility. Accounting for this temporal relationship should ensure less biased regression results.

Like clearances, impoundments appear associated with broader neighborhood conditions. The NB RW(1) model estimates that a percentage point gain in property value correlates with a 1.3% increase in the number of impoundments (95% CI 0.6 to 2.0), net of other parameters (Figure

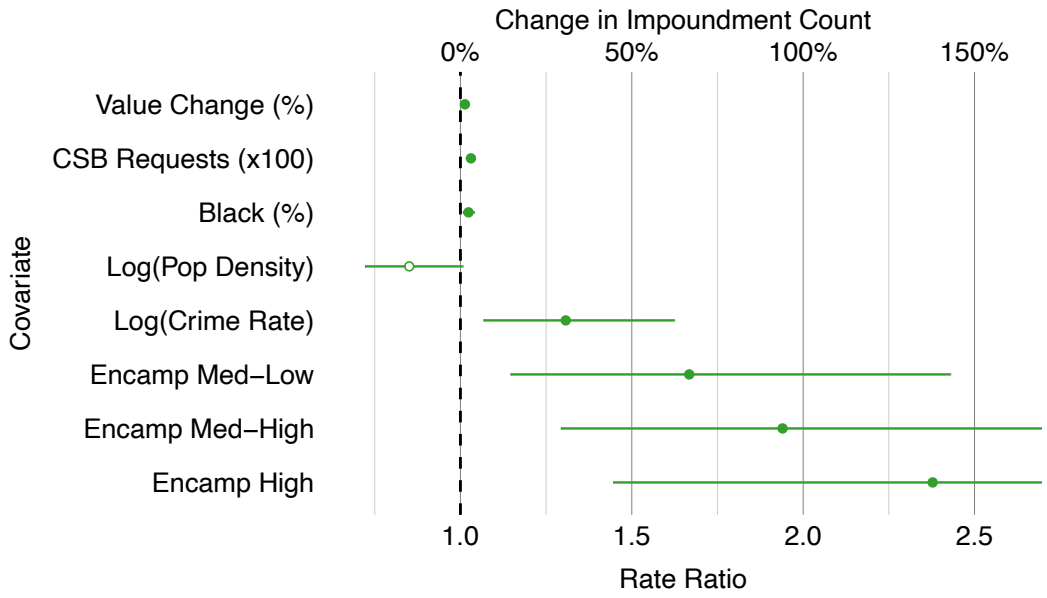

Figure 10. *Posterior medians and 95% credible intervals for impoundments CAR model.*

10 and Table A4).[13] An additional hundred CSB requests raises the predicted count by 3.1% (95% CI 2.1 to 4.0); and a percentage point increase in crime rates exacerbates removals by 30.7% (95% CI 6.7 to 62.4). Interestingly, a point gain in the percentage of Black residents drives up the estimated count by 2.3% (95% CI 0.7 to 4.0).[14] Compared to neighborhoods with low levels of encampments, those with medium-low concentrations witness an estimated 66.7% more impoundments (95% CI 14.6 to 142.9%). This difference grows for higher camp concentrations, though with pronounced uncertainty around estimates. Furthermore, adding this variable barely improves model fit (DIC 3250.16 versus 3251.36; RMSE 10.49 versus 10.87), suggesting a potentially weak association between visible homelessness and spatial removal. Albeit less significant ($p < 0.1$), the negative association for population density also appears notable. Vehicle residents may disproportionately sleep in less populated areas due to lower competition for parking.

[13] Alternative models suggest a negative (but near zero) association between total value and impoundments. The interaction between composite value and change in value also appears non-significant (Table A8).
[14] Replacing Black with White residents results in a negative but non-significant effect (Table A9).

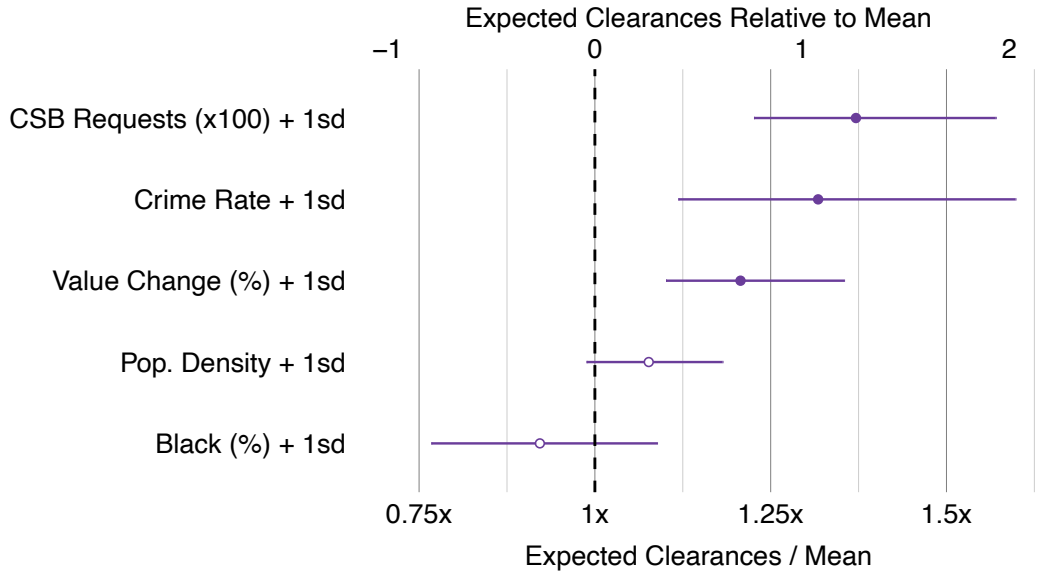

Figure 11. *Expected clearance counts for hypothetical scenarios*. Simulations are based on 1000 draws from posterior distributions. All counterfactuals hold encampment prevalence at medium-low and other covariates at their mean values. Bars indicate 95% CI.

These social and economic factors could contribute to profound differences in policing across Seattle given the existing variation in neighborhood conditions. In Figure 11, I simulate whether raising a variable's value by one standard deviation corresponds to more or less removals compared to the average neighborhood, holding other characteristics equal. Amongst CRAs with medium-low levels of encampments,[15] increasing the change in property value from a mean of 9.1 to 15.2% results in 20.7% more sweeps. Raising the number of CSB requests (from 1040 to 1606) increases clearances by 37.1%, while shifting crime rates (8622 to 13499) grows the expected count by 31.7%. Densifying a neighborhood (7721 to 11365 people per sq. mile) results in 7.7% more sweeps, significant at an alpha level of 0.01. The magnitude of these impacts suggests markedly uneven exposure to spatial removal throughout the city. As anticipated, the consequence of changing racial composition remains consistent with a null effect.

[15] I choose medium-low instead of low in order to better approximate a "typical" neighborhood. This category also helps visualize that these associations persist in CRAs without high levels of homelessness.

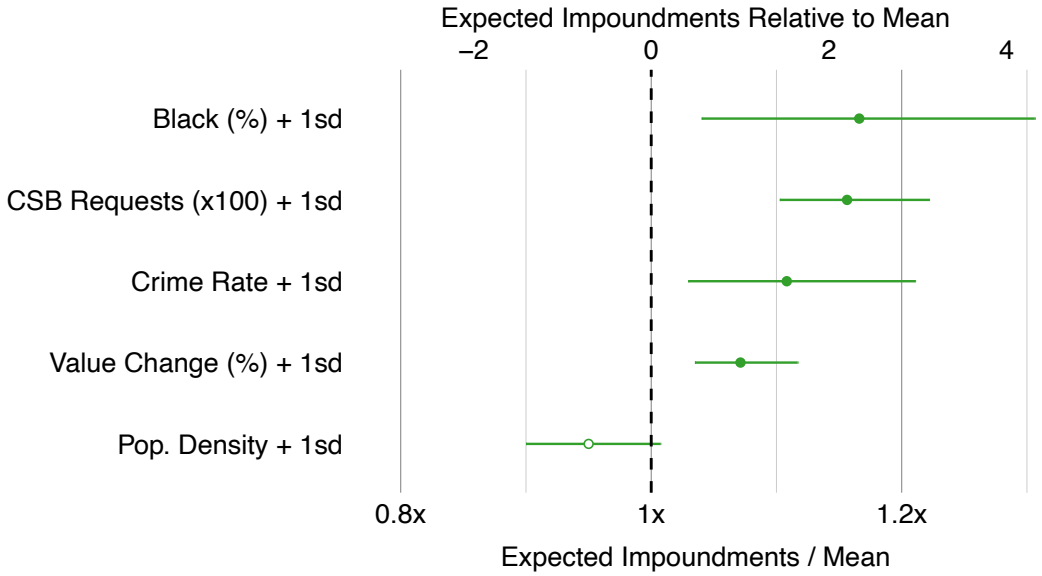

Figure 12. *Expected vehicle removal counts for hypothetical scenarios.*

I similarly anticipate an unequal burden in vehicle impoundments across CRAs. Given a medium-low level of encampments, neighborhoods with value changes one standard deviation above the mean (16.1 versus 9.8%) will experience 7.1% more impoundments compared to average (Figure 12).[16] Unlike with sweeps, shifting the percentage of Black residents (8.5% to 16.4%) results in a statistically significant gain of 16.6% removals. Raising CSB requests (983 to 1550) affects a 15.6% difference, while increasing the crime rate (8717 to 13484) leads to 10.8% more impoundments relative to the mean. In contrast, densifying the population (7664 to 11275) reduces expected counts by 5.0%, which appears significant at an alpha level of 0.10. Sensitivity analyses suggest that the AR(0) and AR(1) models provide similar estimates and uncertainties for each scenario (Table A4 and Figures A8-A9).

Even after accounting for Seattle's widespread growth, economic expansion still appears predictive of policing. Figure 13 depicts expected clearance counts for neighborhoods that gained

[16] The size of one standard deviation will differ between the sweep and impoundment scenarios given that vehicle removal data contains an additional year (2014).

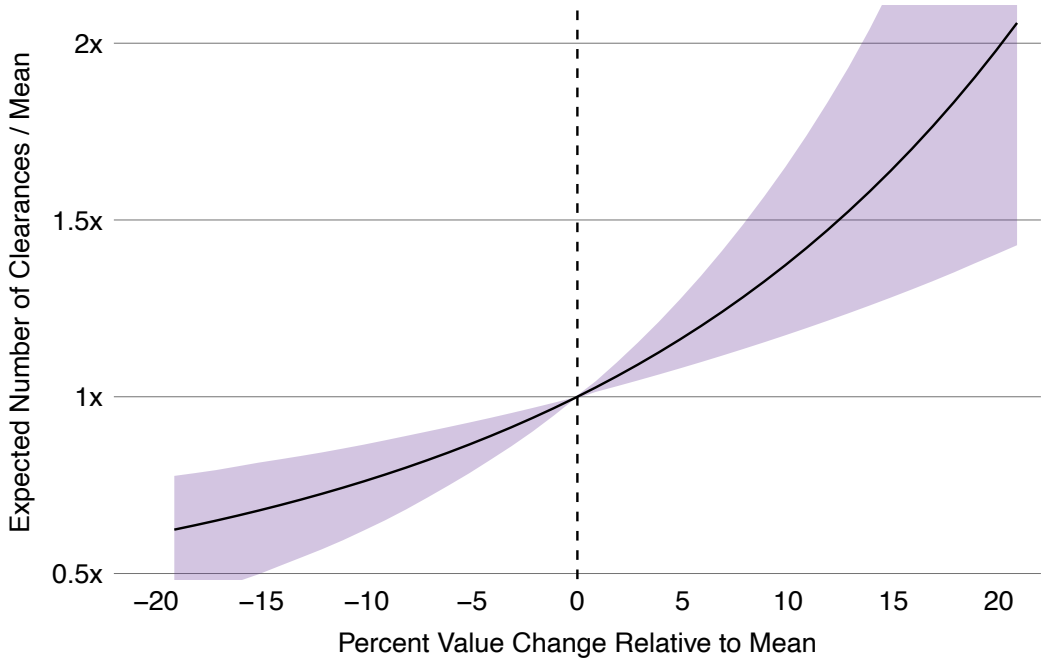

Figure 13. *Expected clearance counts based on shifts in property value*. Simulations are based on 1000 draws from posterior distributions. The scenario compares focal variables to observed means in CRAs with medium-low encampments. Ribbons indicate 95% CI.

a lower or higher percentage of property value compared to the average CRA, holding other variables constant. Given a medium-low level of encampments, raising the mean change in value by 10 points (9.1 to 19.1%) increases sweeps by nearly 40% relative to the average count (Figure 13). Conversely, shifting by 10 fewer points (in this case, losing 0.9% of value) decreases clearances by 25%. I similarly expect 12% more impoundments in neighborhoods with gains in property value 10 percentage points above the mean (19.8 versus 9.8%). In contrast, an equivalent shift downward (losing 0.2% of value) lowers the estimated number of vehicle removals by nearly 10%. As anticipated, the 95% credible intervals do not span a null effect ("1x") at any change in value, suggesting a positive relationship between economic expansion and policing of unsheltered homelessness. Even if not undergoing contraction, CRAs that grow less than the mean neighborhood will still experience fewer removal events – all else equal.

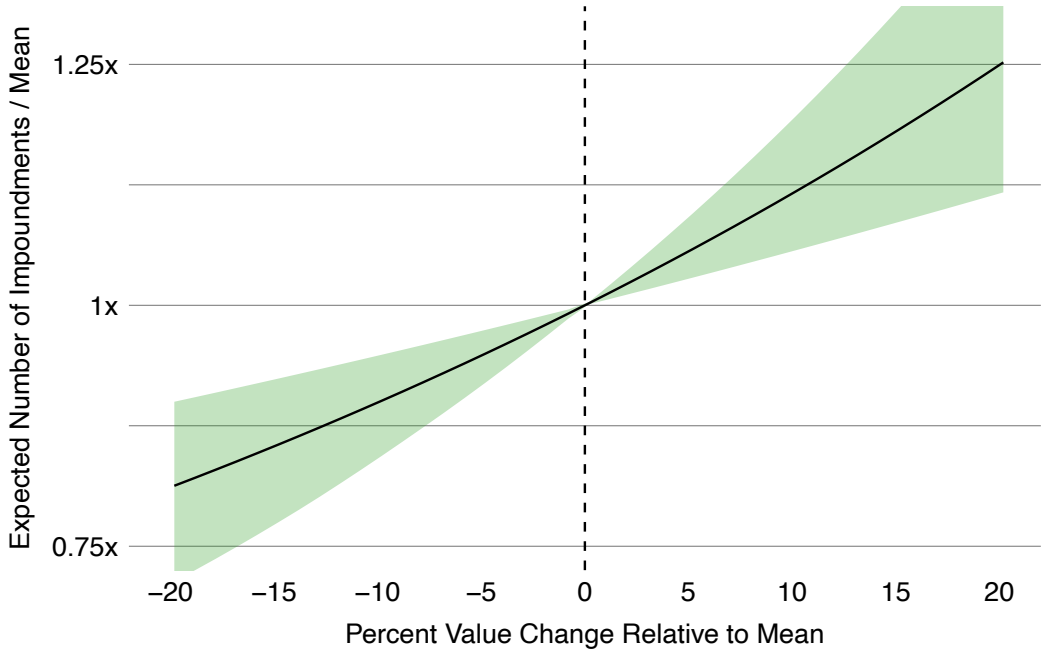

Figure 14. *Expected impoundment counts based on shifts in property value.*

Given the significant effects of neighborhood covariates, estimated counts of removal vary widely across CRAs. In 2023, for example, the NB AR(0) model predicts nearly 300 sweeps in Ballard, followed by almost 100 in both Capitol Hill and Duwamish/SODO (Figure 15, see Figure A12 for all years).[17] However, I estimate less than one clearance in locations around Arbor Heights (southwest) and Seward Park (southeast). The NB RW(1) model produces similar patterns for vehicle removals, although the range in counts appears smaller (Figure 16). Impoundments notably concentrate around SODO, Georgetown, and Ballard, all of which contain less densely populated industrial districts. Comparing these trends to encampment prevalence (Figure 3) again reaffirms that visible homelessness alone does not predict policing. Neighborhoods like Wallingford witness less intervention than expected, while others prove particularly exposed (e.g., Greenwood). My results ultimately suggest that additional factors could help explain these discrepancies.

[17] I also map coefficients of variation (CV), which represent the ratio of the standard deviation to the mean. Uncertainty around estimates appears greatest in CRAs with low counts, few neighbors, or rates that differ from surrounding areas.

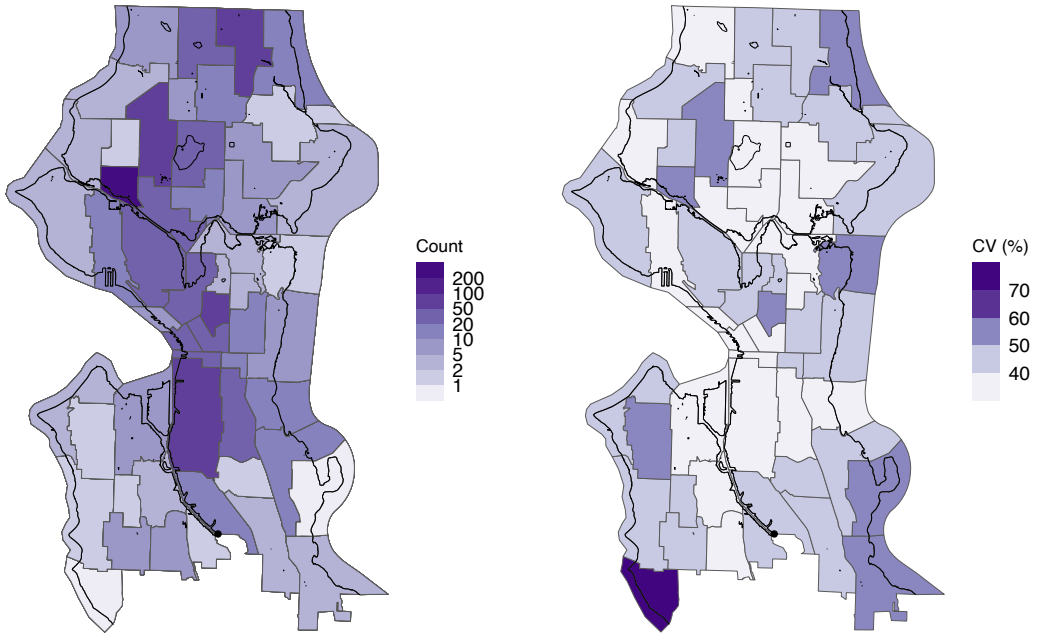

Figure 15. *Posterior median estimates and coefficients of variation (CV) for clearances in 2023.*

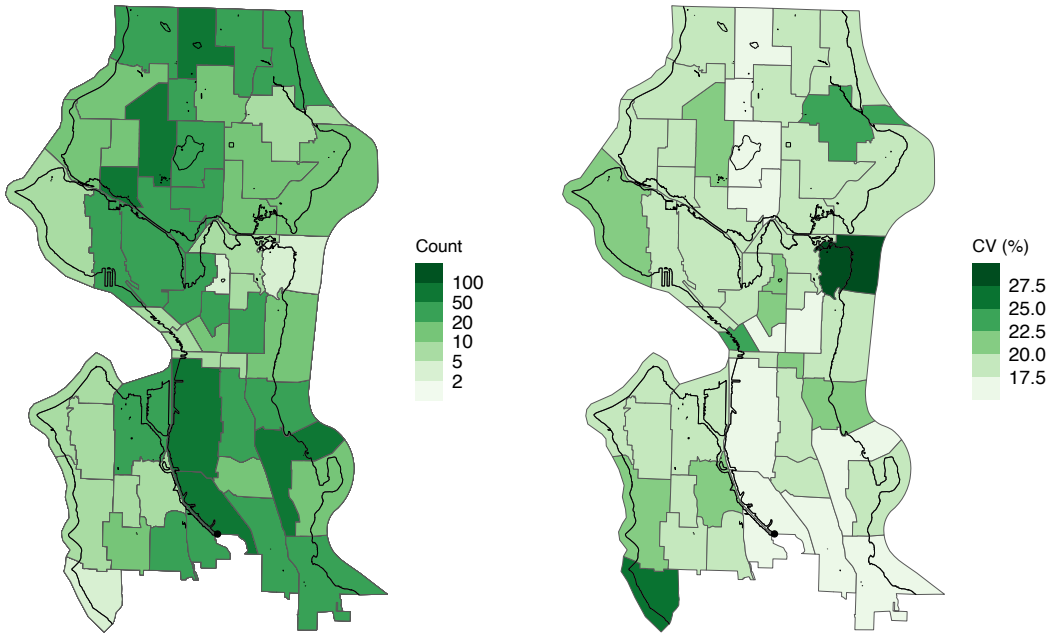

Figure 16. *Posterior median estimates and coefficients of variation (CV) for impoundments in 2023.*

Discussion

My findings extend prior theory on social control, neoliberal urbanism, and cities as growth machines, suggesting that the policing of disorder could partly reflect economic concerns. Remarkably, the prevalence of homelessness in a neighborhood may not substantially influence the forced displacement of unsheltered residents. Instead, spatial removal seems related to broader contextual factors. Most notably, I demonstrate that law enforcement tactics align closely with real estate dynamics, specifically growth in property value. Customer service requests also strongly predict interventions, highlighting the increasingly public-driven nature of punishing poverty. Encampment and vehicle removals additionally reflect crime patterns – underscoring a complex relationship that demands further investigation. Furthermore, I offer evidence that existing racial and spatial disparities shape this exposure to state-sponsored violence.

Seattle does not enforce anti-camping or -parking ordinances equitably across neighborhoods. Although authorities undoubtedly manage homelessness through spatial removal, the scale of interventions in a location does not mirror the concentration of unsheltered residents. As previously mentioned, the spatial distribution of visible homelessness could moderate exposure to law enforcement contact. By including a proxy for this variable, I can more robustly test scholars' claims that policing correlates with economic conditions (Collins et al. 2022; Goldfischer 2020). However, I find that the prevalence of encampments does not significantly predict sweeps nor substantially improve models of impoundments. Although point estimates indicate strong positive associations, the uncertainty around these effects proves substantial. As researchers continue improving the enumeration and mapping of homelessness,[18] I encourage future studies to incorporate more precise spatial and temporal measures of population size.

[18] The Los Angeles Enumeration and Demographic Survey (Ward, Garvey, and Hunter 2024) and King County respondent driven sampling (Almquist et al. 2025) offer promising examples.

Regardless of homeless prevalence, spatial removal disproportionately targets neighborhoods undergoing economic expansion. We expect more sweeps and impoundments in areas that experience higher gains in property value, holding all else equal. Even minimal contraction (e.g., a 1% loss in value) results in substantial declines in events compared to the average CRA. Such findings reinforce past research on neoliberal urbanism (Collins et al. 2022; Peck et al. 2009) and cities as growth machines (Beck 2020; Logan and Molotch 1987), suggesting that policing practices may complement efforts to increase profit and revenue. In residential areas, for example, removal might facilitate real estate development. While in industrial and commercial zones, clearing visible signs of poverty could encourage consumption, commodification, and investment. By leveraging tax data, I importantly assess how law enforcement grows entangled with urban change across this broad range of spaces where people sleep unsheltered.

In addition to economically motivated, the governance of homelessness appears publicly driven. I observe that sweeps and impoundments positively correlate with homelessness-related service requests, thus corroborating prior research on complaint-oriented policing (Beck 2020; Herring 2019). In this context, housed residents increasingly act as surveillance nodes that help authorities locate and punish alleged offenders. Although my study does not evaluate the content of these requests, Beach (2024) notes that *Find It, Fix It* reports frequently advocate for the forced removal of unhoused community members. Application users often express worries about the diminishing use value of their homes, even if they do not voice concerns about long-term sale prices. Unfortunately, I do not test whether complaints affect the prioritization of sites for removal. However, among neighborhoods with comparable sociodemographic characteristics and levels of visible homelessness, these requests appear predictive of intervention. Future studies might evaluate how these complaint infrastructures interact with other neighborhood conditions.

Sweeps and impoundments also correlate with crime, though the mechanisms behind this relationship remain less clear. In locations with greater (reported) illegal activity, heightened police presence could offer more opportunities for enforcing anti-homeless ordinances. Yet this pattern might also highlight processes of urban renewal, given that revitalization seems associated with increased policing and documented offenses (Beck 2020; Cahill et al. 2017; Smith et al. 2021). Unfortunately, my unit of analysis (CRAs) does not allow me to test official claims that clearances promote public safety by targeting sites with criminal histories (City of Seattle 2024b). Admittedly, a study in Denver recently observed high clustering of crime near encampments prior to displacement, potentially suggesting a reactive relationship between sweeps and perceptions of risk (Padmanabhan et al. 2024). However, the authors demonstrate that clearances do not consistently reduce nearby crime and may instead exacerbate violence in surrounding areas.

Interestingly, sweeps target more densely populated neighborhoods, although this association appears weak. In Seattle, encampments and rental units demonstrate similar proximity to amenities, such as grocery stores and transit stops (Sutton et al. 2025). Given a plausible correlation with businesses and public facilities, population density might simply capture the distribution of homelessness after controlling for encampment prevalence. Relatedly, the variable may reflect pressures to reduce visible disorder in commercial districts. Furthermore, people might face difficulties finding concealed locations to camp, thus garnering more attention from authorities. Encampments in these neighborhoods may also obtain higher prioritization scores for obstructing sidewalks and rights-of-way. In contrast, impoundments weakly correlate with lower population densities. This pattern could simply reflect the spatial dispersion of the population, especially for oversized vehicle residents who may disproportionately sleep in liminal zones with more space for parking, such as the industrial districts of SODO, Georgetown, and Ballard.

Lastly, the racial composition of neighborhoods may influence exposure to spatial removal. Although neither intervention correlates with the percentage of White residents, impoundments disproportionately affect CRAs with larger Black populations. For example, I estimate high counts of vehicle removals in Colombia City, North Rainier, and Mt. Baker – areas with sizeable Black communities that have also experienced gentrification (Hwang 2020). Unfortunately, this study does not specifically evaluate whether long-term demographic shifts preempt or follow spatial removal. Nevertheless, this pattern could reflect disproportionate patrolling and surveillance by police in Black neighborhoods, as documented across numerous US cities (Chen et al. 2023). This heightened presence could feasibly increase enforcement of camping and parking restrictions, consequently priming areas for future investment and development.

Conclusion

The policing of homelessness appears deeply embedded in broader processes of urban transformation across Seattle. Desires to reduce visible disorder likely inform these practices, as cities seek to remove perceived obstacles to growth and development. Yet the prevalence of homelessness does not alone predict intervention. Other characteristics of the surrounding environment may determine whether authorities forcibly displace unsheltered residents. Most notably, sweeps and impoundments disproportionately target neighborhoods undergoing economic expansion, holding all else equal. Patterns of spatial removal may even reflect existing racial disparities in law enforcement contact, especially in areas that recently experienced gentrification. Furthermore, members of the public seem to play an active role in these responses by submitting complaints to municipal agencies. Altogether, law enforcement contact does not remain equitably distributed across neighborhoods, but instead dependent on their social and economic conditions.

Interrogating the relationship between neighborhood change and order maintenance policing remains a complex yet necessary task. Sweeps and vehicle impoundments represent increasingly common practices that nevertheless remain understudied. By leveraging novel administrative data, I try to establish a foundation upon which to explore predictors of these interventions. Furthermore, my paper potentially represents the first to control for the spatial distribution of unhoused populations. Although encampment prevalence serves as a crude proxy for visible homeless, accounting for this variable helps isolate the effects of other factors. Importantly, my study also models an approach for evaluating industrial districts, where people increasingly sleep unsheltered. Scholars interested in social control and urban transformations should consider land and improvement values as promising alternatives to housing-based metrics.

Moving forward, studies might leverage more granular geographic and temporal scales to evaluate whether spatial removal precedes or follows complaints, demographic change, and other indicators. Such research will further clarify the motivations behind the criminalization of unsheltered residents. Regardless, forced displacement remains an inhumane and reactive method that can jeopardize safety, worsen health, and sever service connections. Instead, cities should invest in solutions evidenced to bring people indoors and prevent homelessness. As an interim step, governments might allocate space for authorized camping and parking, thereby providing some stability for people trying to exit the streets. Such countermeasures prove urgent amidst recent federal and local decisions to sanction criminal penalties for public camping and other quality-of-life offenses (Grants Pass v. Johnson 2024; Beekman 2024). Ultimately, scholars should examine how communities have successfully contested the carceral logics that punish individuals for structural failures. Engaging with such cases could provide valuable insights into ensuring human rights to security and housing amidst growing pressures to extract profit from urban landscapes.

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Appendix

Reference Map

Figure A1. *Community Reporting Areas in Seattle, WA*. Labels provide neighborhood names.

Exploratory Analysis

Exploratory temporal and spatial tests help inform the construction and interpretation of the final statistical models. I first evaluate serial dependencies in the demeaned and detrended time series for each focal variable using autocorrelation and partial autocorrelation functions (ACF and PACF, respectively). The median neighborhood displays no significant first period lags for sweeps (Figure A2), vehicle removals (Figure A3), or shifts in property value (Figure A4). These findings suggest that the observed data does not follow a first order autoregressive process, whereby a CRA's count of removals correlates with that of the prior year.

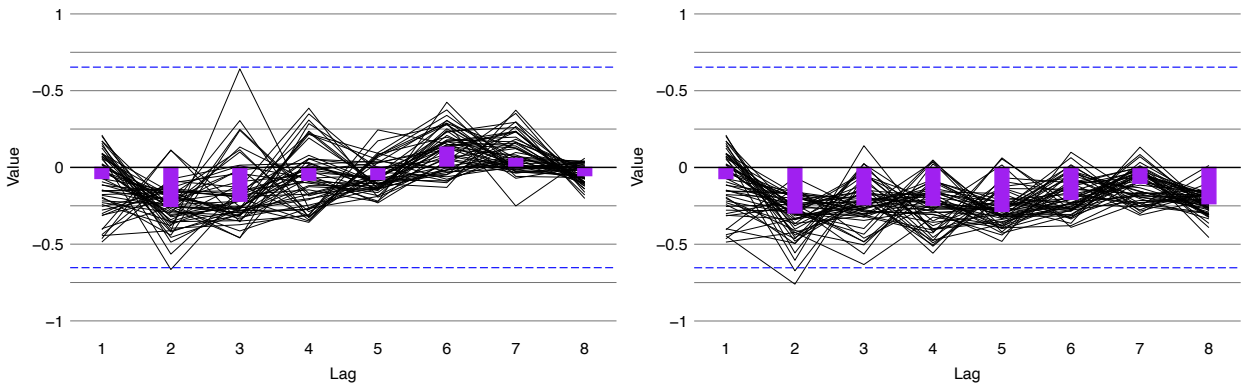

Figure A2. *ACF (left) and PACF (right) correlograms for sweeps*. Lines represent demeaned/detrended CRA time series. Purple bars signify median values. Blue dashes mark statistical significance ($p < 0.05$).

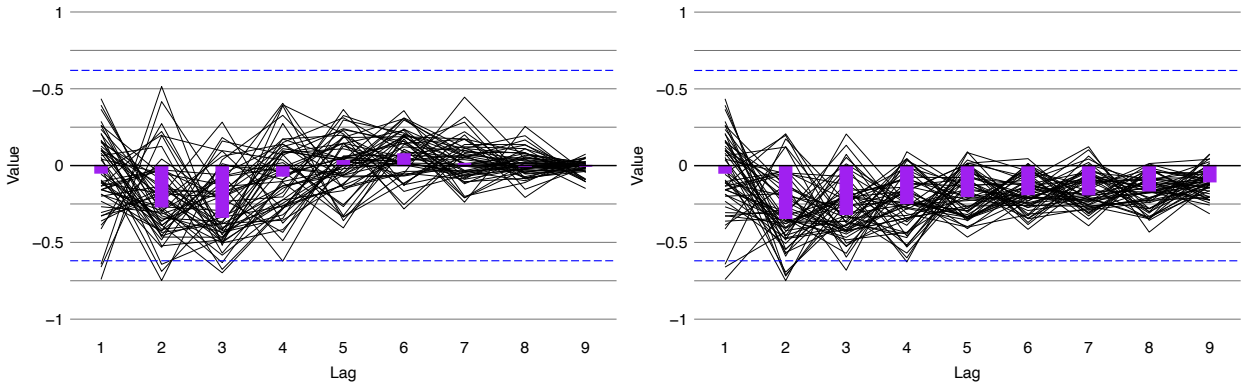

Figure A3. *ACF (left) and PACF (right) correlograms for impoundments*.

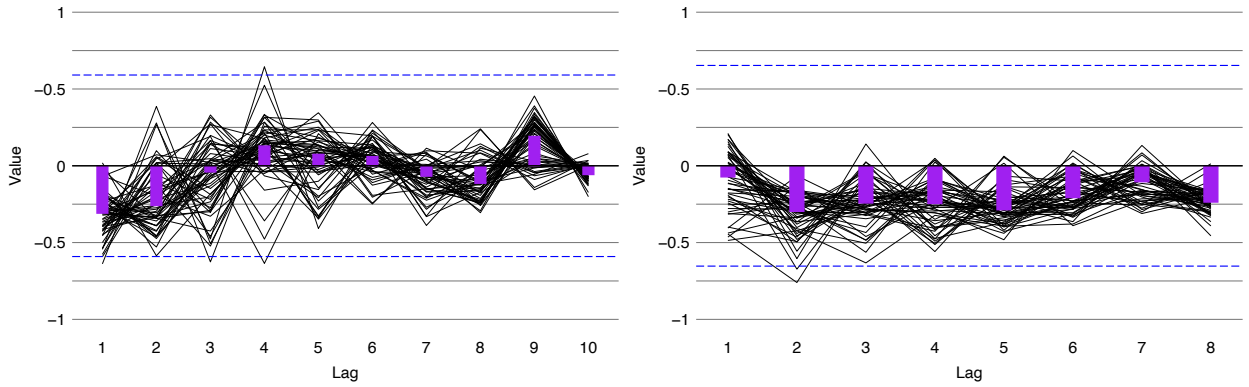

Figure A4. *ACF (left) and PACF (right) correlograms for percent change in property value.*

Accordingly, I fit non-temporal AR(0) models on the demeaned and detrended time series of my focal variables. Ljung-Box tests suggest that residuals for most CRAs only contain white noise (Figure A5). Although more neighborhoods indicate serial correlation for vehicle removals, the proportion remains small. I also do not worry about significant temporal confounding for property value as a predictor variable. Moreover, residuals appear normally distributed for each outcome, thus not violating model assumptions.

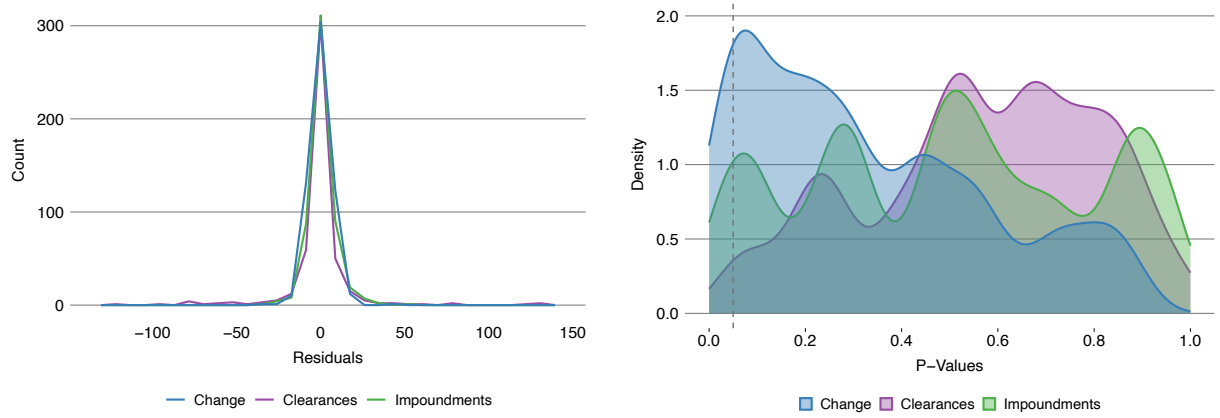

Figure A5. *Distribution of AR(0) models' residuals (left) and Ljung-Box test results (right) for focal variables.* P-values above 0.05 suggest only white noise remains in residuals.

I thereafter use Generalized Linear Models (with covariates) to determine appropriate distributions and spatial processes. For clearances, a Poisson regression demonstrates overdispersion (ratio = 21.2, χ = 9918.0, p < 0.001), with a higher observed variance than assumed. As such, I fit

Zero-Inflated Poisson (ZIP), Negative Binomial (NB), and Zero-Inflated Negative Binomial (ZINB) models. I unsurprisingly prefer the NB over Poisson per the Likelihood Ratio test (χ = 5743.4, $p < 0.001$). A Vuong test further indicates that the NB performs better than the ZIP ($p < 0.001$) and ZINB ($p < 0.05$). A Poisson regression for impoundments also displays overdispersion (ratio = 7.0, χ = 3360.7, $p < 0.001$), while the NB offers improved fit over the ZIP ($p < 0.001$) and ZINB ($p < 0.05$). Lastly, Moran's I tests on the preferred NB models suggest significant spatial correlation in the residuals for sweeps and impoundments ($p < 0.001$). In a given year, a CRA's removal count helps predict those of adjacent neighborhoods. I should thus account for this spatial dependence in order to better isolate the effects of explanatory variables.

Model Comparisons and Results

With the *bmstdr* package (Sahu et al. 2023), I calculate choice criteria and validation statistics for various conditional autoregressive models (Tables A1 and A2). These specifications differ in their distributions (e.g., Negative Binomial, Poisson, and zero-inflated versions), as well as time parameters (e.g., non-temporal, autoregressive, and random walks). Lower Deviance and Watanabe–Akaike Information Criterion values (DIC and WAIC, respectively) indicate better in-sample fit. Smaller Root Mean Squared Errors (RMSE) and Mean Absolute Errors (MAE) suggest greater out-of-sample accuracy. Higher coverage (CVG) reflects the proportion of credible intervals that contain the observed out-of-sample values. Here, I perform K-fold cross-validation based on 2000 Markov chain Monte Carlo samples. For robustness, I also visualize the posterior medians and 95% credible intervals for each models' covariates (Figures A7-A9). This appendix additionally includes regression results (Tables A3 and A4) and hypothetical simulations (Figures A10 and A11) for all Negative Binomial models. Lastly, I map the posterior median estimates of sweeps and impoundments for CRAs across the study period (Figures A12 and A13).

Table A1. *Sweeps Model Choice Criteria & Validation Statistics*

Model	DIC	WAIC	RMSE	MAE	CVG
NB AR(0)	2268.98	2275.53	19.72	10.18	36.17
NB AR(1)	1913.52	1918	20.47	6.99	38.30
NB RW(1)	1913.52	1917.86	20.59	7.03	38.30
ZINB AR(0)	2261.41	2270	20.32	10.30	34.04
Poisson AR(0)	3111.13	9963.42	23.03	10.01	12.77
ZIP AR(0)	2580.24	9169.86	23.48	10.67	6.38

Table A2. *Impoundments Model Choice Criteria & Validation Statistics*

Model	DIC	WAIC	RMSE	MAE	CVG
NB AR(0)	3315.28	3316.01	12.50	8.10	49.06
NB AR(1)	3251.95	3255.16	10.54	6.61	62.26
NB RW(1)	3250.16	3253.60	10.49	6.59	62.26
ZINB RW(1)	3234.61	3239.19	11.12	6.84	62.26
Poisson RW(1)	3868.55	4102.27	10.31	6.60	35.85
ZIP RW(1)	3787.98	3996.70	10.75	6.89	37.74

Table A3. *Posterior Median Rate Ratios for Clearance Negative Binomial CAR Models*

	NB AR(0)		**NB AR(1)**		**NB RW(1)**	
Covariate	Median	95%CI	Median	95%CI	Median	95%CI
Value Change (%)	1.046	(1.026 - 1.067)	0.995	(0.981 - 1.009)	0.995	(0.981 - 1.010)
Encamp Med-Low	0.875	(0.431 - 1.791)	1.167	(0.666 - 2.055)	1.174	(0.669 - 2.069)
Encamp Med-High	1.341	(0.622 - 2.875)	2.847	(1.559 - 5.231)	2.875	(1.573 - 5.288)
Encamp High	1.527	(0.589 - 3.967)	4.033	(1.945 - 8.457)	4.087	(1.969 - 8.585)
CSB Requests (x100)	1.081	(1.062 - 1.101)	1.026	(1.012 - 1.039)	1.025	(1.012 - 1.039)
Log(Pop Density)	1.327	(0.965 - 1.783)	1.290	(1.032 - 1.610)	1.291	(1.033 - 1.610)
Black (%)	0.982	(0.950 - 1.015)	0.986	(0.961 - 1.011)	0.986	(0.961 - 1.011)
Log(Crime Rate)	2.393	(1.515 - 3.654)	2.189	(1.617 - 2.930)	2.185	(1.613 - 2.927)

Table A4. *Posterior Median Rate Ratios for Impoundment Negative Binomial CAR Models*

	NB AR(0)		**NB AR(1)**		**NB RW(1)**	
Covariate	Median	95%CI	Median	95%CI	Median	95%CI
Value Change (%)	1.010	(1.004 - 1.017)	1.013	(1.006 - 1.020)	1.013	(1.006 - 1.020)
Encamp Med-Low	1.627	(1.120 - 2.364)	1.665	(1.147 - 2.418)	1.667	(1.146 - 2.429)
Encamp Med-High	1.843	(1.231 - 2.762)	1.926	(1.288 - 2.900)	1.940	(1.293 - 2.930)
Encamp High	2.200	(1.337 - 3.577)	2.356	(1.437 - 3.850)	2.378	(1.446 - 3.898)
CSB Requests (x100)	1.035	(1.027 - 1.042)	1.031	(1.022 - 1.041)	1.031	(1.021 - 1.040)
Log(Pop Density)	0.866	(0.736 - 1.025)	0.851	(0.723 - 1.006)	0.850	(0.721 - 1.006)
Black (%)	1.023	(1.007 - 1.040)	1.023	(1.007 - 1.040)	1.023	(1.007 - 1.040)
Log(Crime Rate)	1.320	(1.077 - 1.640)	1.302	(1.064 - 1.614)	1.307	(1.067 - 1.624)

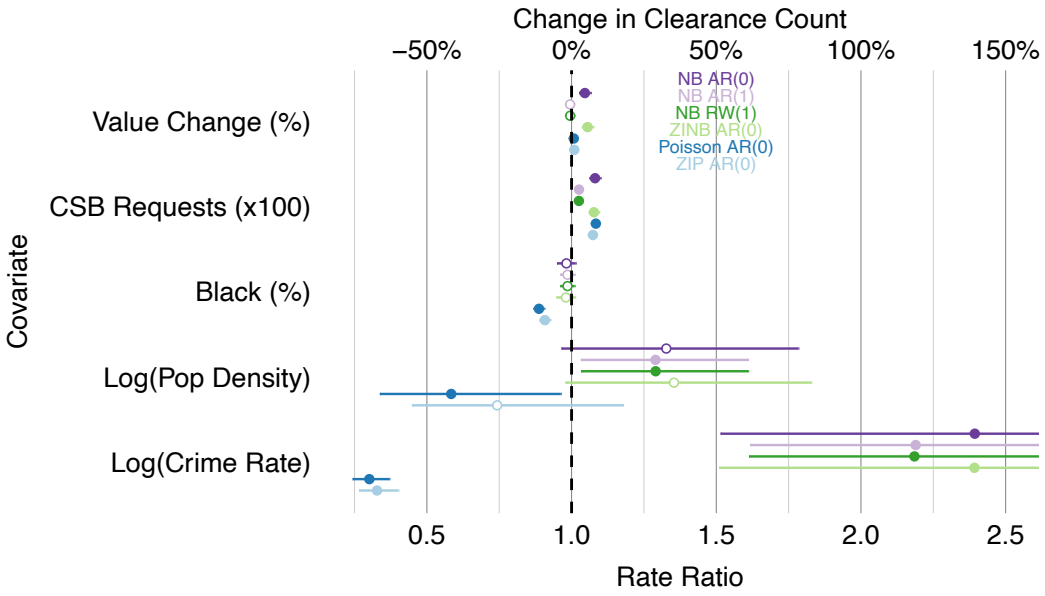

Figure A6. *Posterior medians and 95% credible intervals for sweep CAR models*. Filled circles suggest statistical significance. See following plot for encampment prevalence.

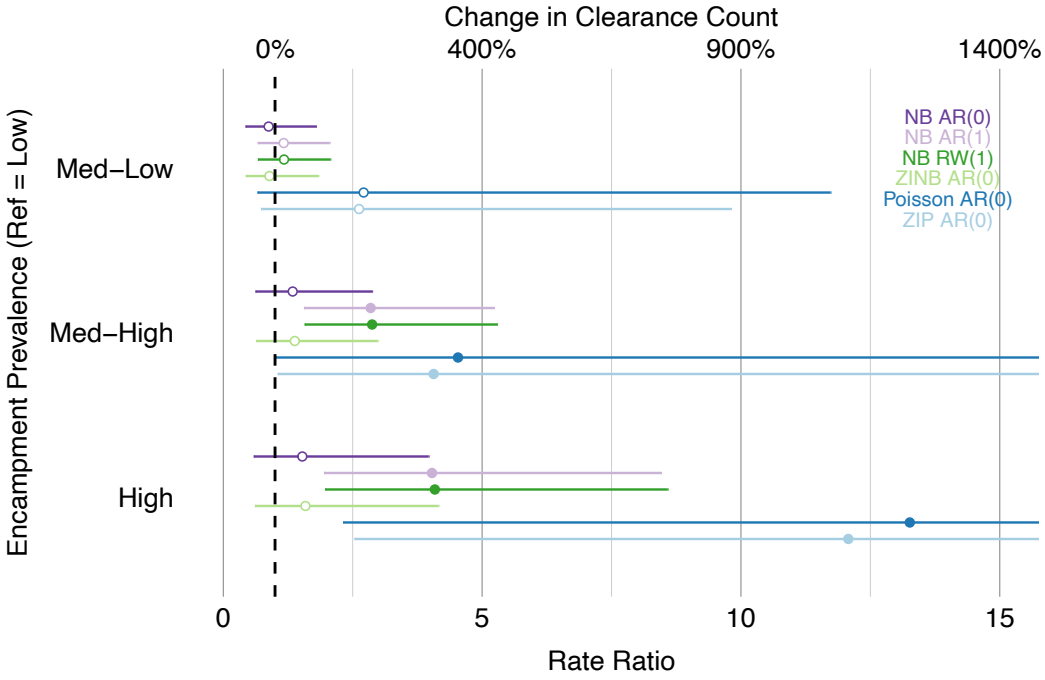

Figure A7. *Posterior medians and 95% credible intervals for sweep CAR models*.

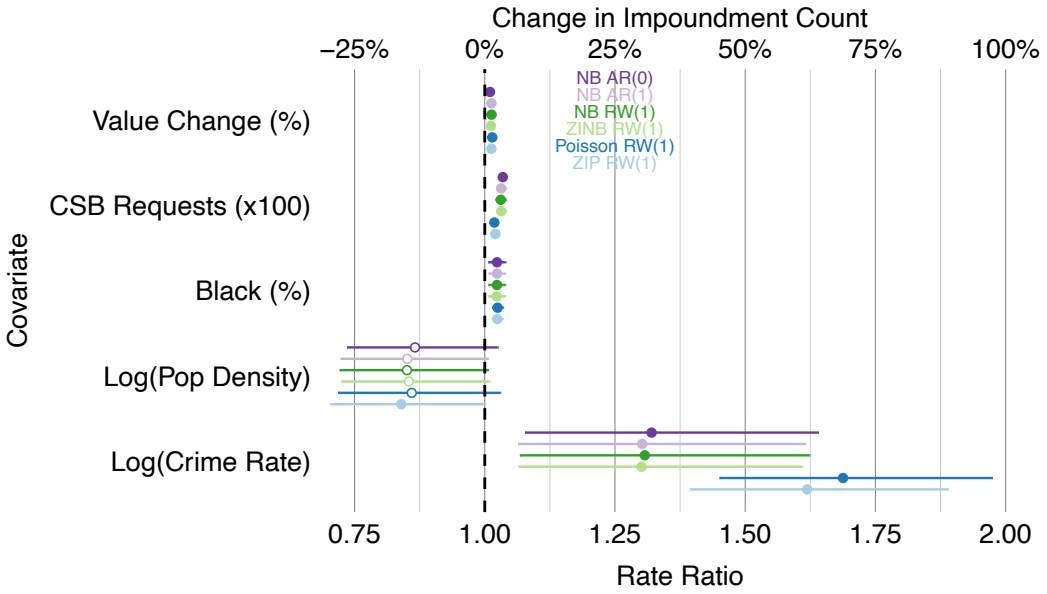

Figure A8. *Posterior medians and 95% credible intervals for impoundment CAR models.* See following plot for effects of encampment prevalence.

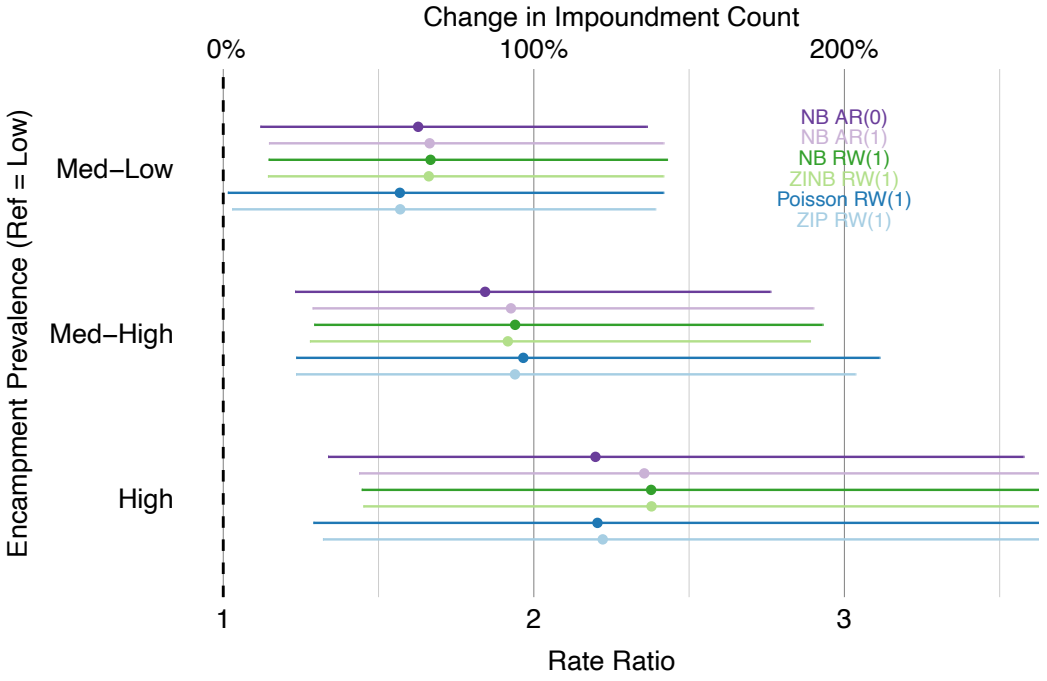

Figure A9. *Posterior medians and 95% credible intervals for impoundment CAR models.*

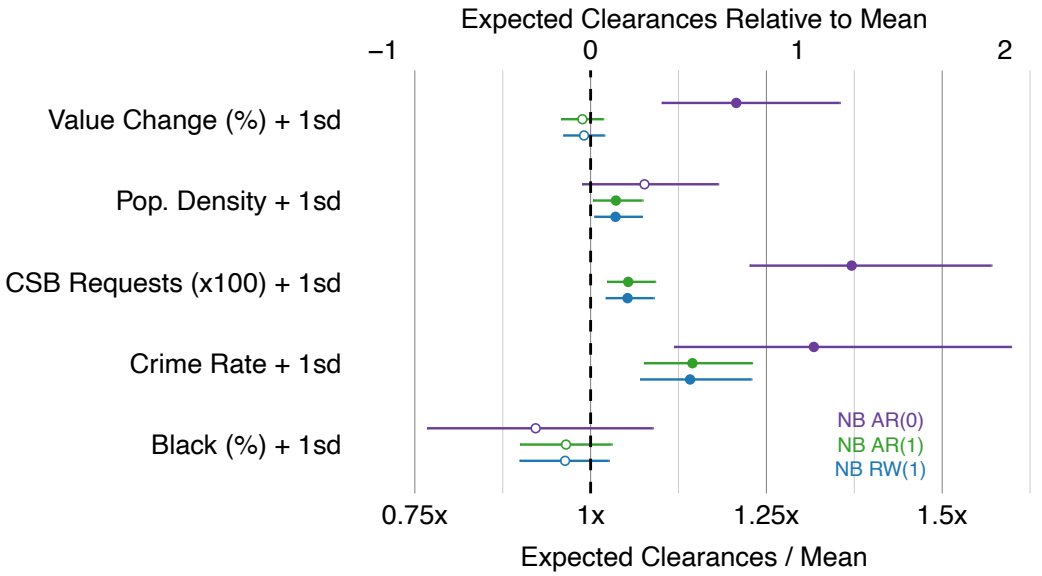

Figure A10. *Expected clearance counts for hypothetical scenarios*. Simulations are based on 1000 draws from posterior distributions. All counterfactuals hold encampment prevalence at medium-low and other covariates at their means. Bars indicate 95% CI.

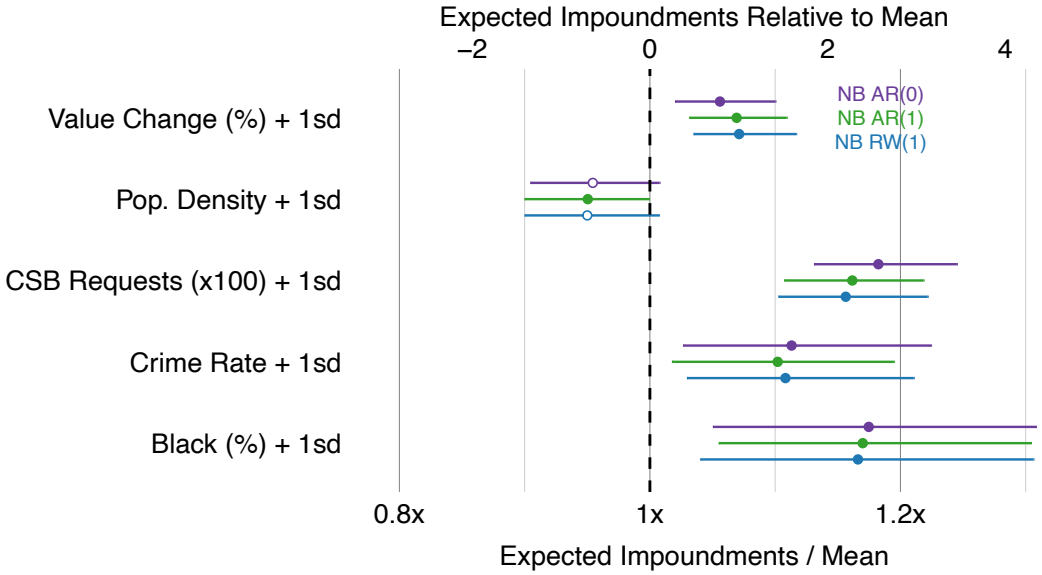

Figure A11. *Expected vehicle removal counts for hypothetical scenarios*.

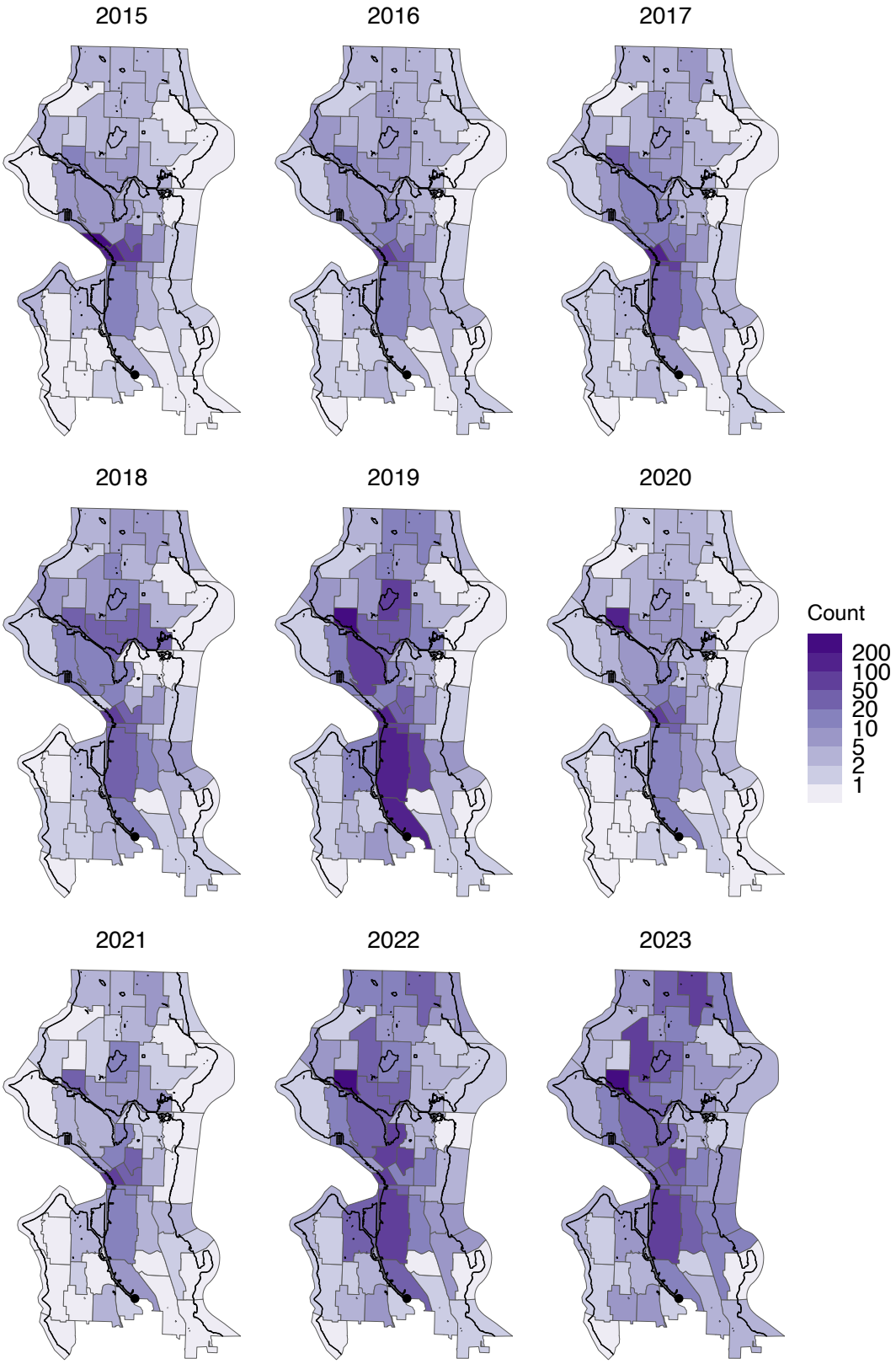

Figure A12. *Negative Binomial AR(0) CAR posterior median estimates for clearances by year.*

Figure A13. *Negative Binomial RW(1) CAR posterior median estimates for impoundments by year.*

Additional Robustness Checks

Table A5. *Posterior Median Rate Ratios for Clearance Negative Binomial AR(0) CAR Models*

	Baseline		Total Value		Total x Change	
Covariate	Median	95%CI	Median	95%CI	Median	95%CI
Value Change (%)	1.046	(1.026 - 1.067)			1.058	(1.027 - 1.090)
Total Value ($100 mil)			1.001	(0.996 - 1.007)	1.003	(0.995 - 1.009)
Total x Change					0.999	(0.999 - 1.001)
CSB Requests (x100)	1.081	(1.062 - 1.101)	1.078	(1.059 - 1.098)	1.079	(1.059 - 1.100)
Log(Pop Density)	1.327	(0.965 - 1.783)	1.273	(0.954 - 1.670)	1.322	(0.967 - 1.773)
Log(Crime Rate)	2.393	(1.515 - 3.654)	2.356	(1.565 - 3.467)	2.434	(1.544 - 3.697)
Black (%)	0.982	(0.950 - 1.015)	0.990	(0.960 - 1.021)	0.982	(0.950 - 1.015)
Encamp Med-Low	0.875	(0.431 - 1.791)	0.909	(0.468 - 1.760)	0.880	(0.436 - 1.785)
Encamp Med-High	1.341	(0.622 - 2.875)	1.420	(0.689 - 2.887)	1.355	(0.632 - 2.880)
Encamp High	1.527	(0.589 - 3.967)	1.563	(0.631 - 3.822)	1.500	(0.578 - 3.906)

Table A6. *Posterior Median Rate Ratios for Clearance Negative Binomial AR(0) CAR Models*

	Baseline		No Prevalence		White	
Covariate	Median	95%CI	Median	95%CI	Median	95%CI
Value Change (%)	1.046	(1.026 - 1.067)	1.046	(1.026 - 1.067)	1.046	(1.023 -1.066)
CSB Requests (x100)	1.081	(1.062 - 1.101)	1.086	(1.068 - 1.104)	1.079	(1.061 - 1.098)
Log(Pop Density)	1.327	(0.965 - 1.783)	1.332	(0.955 - 1.804)	1.190	(0.829 - 1.645)
Log(Crime Rate)	2.393	(1.515 - 3.654)	2.706	(1.796 - 3.856)	2.242	(1.438 - 3.398)
Black (%)	0.982	(0.950 - 1.015)	0.978	(0.946 - 1.011)		
Encamp Med-Low	0.875	(0.431 - 1.791)			0.822	(0.402 - 1.684)
Encamp Med-High	1.341	(0.622 - 2.875)			1.355	(0.634 - 2.881)
Encamp High	1.527	(0.589 - 3.967)			1.535	(0.600 - 3.939)
White (%)					0.991	(0.974 - 1.007)

Table A7. *Choice Criteria & Validation Statistics for Alternative Clearance Models*

Model	DIC	WAIC	RMSE	MAE	CVG
Baseline	2268.98	2275.53	19.72	10.18	36.17
Total Value	2295.31	2301.43	22.04	11.41	31.91
Total x Change	2272.74	2280.18	19.59	10.21	34.04
No Prevalence	2266.56	2272.70	20.03	10.40	34.04
White	2268.30	2274.70	19.04	9.96	34.04

Table A8. *Posterior Median Rate Ratios for Impoundment Negative Binomial RW(1) CAR Models*

	Baseline		Total Value		Total x Change	
Covariate	Median	95%CI	Median	95%CI	Median	95%CI
Value Change (%)	1.013	(1.006 - 1.020)			1.004	(0.994 - 1.015)
Total Value ($100 mil)			0.996	(0.992 - 0.999)	0.996	(0.992 - 0.999)
Total x Change					1.000	(1.000 - 1.000)
CSB Requests (x100)	1.031	(1.021 - 1.040)	1.031	(1.021 - 1.041)	1.033	(1.023 - 1.043)
Log(Pop Density)	0.850	(0.721 - 1.006)	0.865	(0.723 - 1.039)	0.862	(0.729 - 1.025)
Log(Crime Rate)	1.307	(1.067 - 1.624)	1.323	(1.061 - 1.677)	1.277	(1.036 - 1.591)
Black (%)	1.023	(1.007 - 1.040)	1.023	(1.006 - 1.040)	1.023	(1.006 - 1.039)
Encamp Med-Low	1.667	(1.146 - 2.429)	1.692	(1.113 - 2.569)	1.691	(1.148 - 2.498)
Encamp Med-High	1.940	(1.293 - 2.930)	1.942	(1.233 - 3.068)	1.934	(1.270 - 2.964)
Encamp High	2.378	(1.446 - 3.898)	2.651	(1.521 - 4.654)	2.549	(1.518 - 4.328)

Table A9. *Posterior Median Rate Ratios for Impoundment Negative Binomial RW(1) CAR Models*

	Baseline		No Prevalence		White	
Covariate	Median	95%CI	Median	95%CI	Median	95%CI
Value Change (%)	1.013	(1.006 - 1.020)	1.013	(1.006 - 1.020)	1.014	(1.007 - 1.021)
CSB Requests (x100)	1.031	(1.021 - 1.040)	1.033	(1.023 - 1.043)	1.030	(1.020 - 1.040)
Log(Pop Density)	0.850	(0.721 - 1.006)	0.880	(0.736 - 1.054)	0.876	(0.728 - 1.067)
Log(Crime Rate)	1.307	(1.067 - 1.624)	1.578	(1.313 - 1.905)	1.364	(1.104 - 1.712)
Black (%)	1.023	(1.007 - 1.040)	1.021	(1.004 - 1.038)		
Encamp Med-Low	1.667	(1.146 - 2.429)			1.616	(1.085 - 2.426)
Encamp Med-High	1.940	(1.293 - 2.930)			1.884	(1.227 - 2.921)
Encamp High	2.378	(1.446 - 3.898)			2.166	(1.287 - 3.658)
White (%)					0.997	(0.988 - 1.006)

Table A10. *Choice Criteria & Validation Statistics for Alternative Impoundment Models*

Model	DIC	WAIC	RMSE	MAE	CVG
Baseline	3250.16	3253.60	10.49	6.59	62.26
Total Value	3250.96	3253.98	11.09	6.71	60.38
Total x Change	3241.01	3245.07	10.41	6.51	62.26
No Prevalence	3251.38	3254.65	10.89	6.77	60.38
White	3252.76	3256.38	10.54	6.57	58.49