Analyzing the Effect of Crime-Free Housing Policies on Completed Evictions Using Spatial First Differences

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Abstract

Crime-free housing policies attempt to prevent crime within rental properties by enrolling property owners in a local crime-free housing program, which subsequently permits landlords to use a supplemental lease agreement stating certain activities that could lead to a tenant being evicted. Building on third-party policing strategies, crime-free housing policies are widely prevalent across the United States, with an estimated 2,000 jurisdictions adopting them since 1992. Despite the widespread adoption of such policies, no previous research has identified their effect on evictions.

This article analyzes the effect of crime-free housing policies on evictions in four locations (Fremont, Hayward, Riverside, and San Diego County) in California. The authors obtained geocoded data on evictions through Public Records Act requests submitted to sheriff's departments in California seeking writs of execution, with additional Public Records Act requests submitted to municipalities to obtain policy implementation information, including the location of certified multifamily property units. To identify a causal effect, a spatial first differences design was used to exploit variation between U.S. Census Bureau block groups with and without certified properties.

Abstract (continued)

The results show that block groups with crime-free housing certified rental units have lower per capita income and larger proportions of Black and Latin/Hispanic populations. In each location, model results indicate that crime-free housing policies significantly increase evictions. Considered jointly, the findings suggest that crime-free housing policies increase evictions by 24.9 percent (95-percent confidence interval: 15.1–34.6 percent) within treated block groups. Given the harm that evictions cause and the governmental costs of eviction proceedings, municipalities across the United States should weigh the benefits of crime-free housing policies against increases in evictions. In addition, given the close policy similarities between crime-free housing policies, criminal activity nuisance ordinances, chronic nuisance ordinances, and the one-strike policy in public housing, these results indicate that policymakers should consider revising the existing policies as a potential means to reduce evictions nationally.

Introduction

Evictions represent a growing problem in the United States. Between 2000 and 2018, court filings for evictions increased by 21.5 percent to 3.6 million cases annually (Gromis et al., 2022). Housing displacement is a critical pathway to homelessness, causes physical and mental health problems, and exacerbates food insecurity for children (Collinson et al., 2023; Hatch and Yun, 2020; Leifheit et al., 2020; Vásquez-Vera et al., 2017). Evictions disproportionately affect low-income tenants and minority populations, with Black women at the greatest risk of an eviction (Hartman and Robinson, 2003; Hepburn, Louis, and Desmond, 2020). Those costs are not borne solely by individuals; evictions cause broader community harm, including increased emergency room use, hospitalizations, homelessness, and spending on social services (Collinson et al., 2023). The United States outpaces global peers in terms of the percentage of renters evicted, with 6.1 percent of renters in the United States facing eviction proceedings in 2016, compared with less than 2 percent of renters in other Organisation for Economic Co-Operation and Development (OECD) countries (OECD, 2020).

Some local policies nominally motivated by crime prevention may directly increase evictions, such as chronic nuisance ordinances, criminal activity nuisance ordinances, and crime-free housing policies (CFHPs). Those policies penalize property owners who do not evict tenants engaged in certain activities specified by the ordinance. Such ordinances are widely prevalent across the United States: an estimated 2,000 municipalities have a criminal activity nuisance ordinance or crime-free housing policy (Ramsey Mason, 2018). However, to date, limited research has examined the effect of those policies on evictions.

Crime-free housing policies are particularly important to evaluate, given the enforcement mechanism the policy uses to attempt to prevent crime. CFHPs are municipal programs that certify multifamily housing units as crime-free once property owners attend a training offered by law enforcement agencies, make specific physical modifications to their units, and add a supplemental lease addendum to their standard rental agreement. The supplemental lease addendum is the policy's primary enforcement mechanism, permitting property owners to evict a tenant for engaging in or facilitating any criminal behavior (Archer, 2019).[1]

Although CFHPs use evictions as a tool to enforce the policy, calculating the magnitude of the effect is critical because it could inform municipalities' choice to adopt or maintain CFHPs. If CFHPs substantially increase evictions, municipalities will need to weigh the desired policy outcomes of CFHPs against the subsequent social and governmental costs of additional evictions.

This article estimates the effect of crime-free housing policies on evictions, using a newly constructed database on writs of execution across the state of California between 2017 and 2021. To analyze that effect, this study uses a spatial first differences research design (Druckenmiller and Hsiang, 2018) that allows for the estimation of causal effects using cross-sectional data containing small area observations. The data used in the analysis—writs of execution records and CFHP implementation information—were obtained using Public Records Act requests submitted to municipalities and government agencies throughout the state of California. The present spatial first difference design uses block-level variation in the number of CFHP-certified rental units to identify the effect of crime-free housing policies on evictions in four locations in 2019 (Fremont, Hayward, Riverside, and San Diego County). The findings indicate that neighborhood blocks containing CFHP-certified rental units have a significantly higher number of evictions, increasing the average amount by 24.9 percent (95-percent confidence interval: 15.1–34.6 percent) across studied locations.

Challenges in Obtaining Eviction Data in Municipalities

Evaluating the effect of existing policies on evictions is difficult due to the lack of reliable, systematic data on evictions and housing policies at the local level (Goplerud and Pollack, 2021). Although some data on evictions exist, such as the database maintained by The Eviction Lab at Princeton University, those measures frequently are collected only at the state or county level, limiting the use of statistical methods to evaluate the effect of local policymaking on evictions (Gromis et al., 2022). Further, those eviction databases typically rely on measures obtained from court filings, which have substantial limitations. For instance, court filing data frequently do not contain the outcome of a case (i.e., whether the filing led to an eviction or was the cause of the eviction), may contain substantial duplicate counts due to landlords using serial filings to collect rent, or could be unavailable in a jurisdiction due to records being sealed to protect tenants (Garboden and Rosen, 2019; Goplerud and Pollack, 2021; Porton, Gromis, and Desmond, 2021).

Obtaining records on evictions in cities and localities, particularly on completed evictions, could provide the evidence needed to evaluate the effects of local policymaking. One such measure of evictions that is available across jurisdictions is writs, which are orders issued by courts to landlords following both an unlawful detainer action decided in favor of a landlord and a notice to vacate provided to a tenant. Writs permit landlords to pursue a "lockout" (forcible removal of a

[1] The definition of *criminal behavior* is not explicitly defined in the lease addendum, although the addendum notes that "proof of violation shall not require a criminal conviction, but shall be by a preponderance of the evidence" (ICFA, n.d. b.).

tenant by a county sheriff) if the renter does not voluntarily vacate the unit.[2] To do so, landlords provide the writ to a sheriff's office to schedule a lockout; on the scheduled date, a sheriff will remove the tenant from the rental unit. Those actions—scheduled and completed writs—are recorded by the sheriff's departments and can be obtained through Public Records Act requests.

Writs of execution records contain benefits and limitations as a measure of evictions compared with alternative records, such as eviction notices or court filings for unlawful detainer proceedings. Whereas eviction notices and filing records may or may not have led to a completed eviction, writ records correspond directly to known completed evictions. Conversely, because writs are issued only when a tenant has not voluntarily vacated a unit, writ records will necessarily underestimate the total number of evictions occurring in each location. However, underestimation is an issue with all eviction measures, including notices and filings, because informal or illegal evictions are not recorded in administrative records. In addition, writs of execution records may be the only available measure of evictions within smaller geographies, such as municipalities or neighborhood blocks. For example, most records on eviction filings in California have been sealed due to state law (AB2819),[3] making writs of execution one of the only measures available for evaluating municipal policies.

Policy Background and Components

Crime-free housing policies originated in a program started by the Mesa Arizona Police Department in 1992 with the stated purpose of reducing "spiraling crime rates in the city's numerous apartment communities" (Zehring, 1994). CFHPs attempt to achieve that goal by enrolling local landlords in the program, which entails three primary components: trainings provided to landlords on compliance with the program; requirements for landlords to modify their rental units to comply with crime prevention through environmental design (CPTED) standards; and a supplemental lease agreement for landlords to include as part of their standard lease, stating that tenants can be evicted from their unit if they are suspected of any criminal activities (Archer, 2019; Ramsey Mason, 2018).

CFHPs have extended to other jurisdictions through the efforts of the International Crime Free Association (ICFA), a nonprofit organization that produces model policy documentation for CFHPs and markets the policy to law enforcement agencies (ICFA, n.d.a.). To implement the policy in additional jurisdictions, the ICFA conducts 3-day conferences with law enforcement officers to train them on the implementation of CFHPs in their local jurisdictions. The organization also provides agencies with instruction materials for training landlords, CPTED inspection forms, signs to display outside certified rental units, marketing materials, program logos, and supplemental lease agreement language.

The ICFA describes the program as using a three-phase approach to eliminate crime in multifamily housing units (ICFA, n.d.a.). First, the policy aims to train landlords and property managers on

[2] The specific name of the writ corresponding to an eviction lockout can vary depending on the jurisdiction. For example, Washington State refers to them as "writs of restitution," whereas California uses both "writ of possession" and "writ of execution" to refer to eviction lockouts.

[3] "Unlawful Detainer Proceedings," CA AB2819, 2015–2016 Regular Session (CA, 2016). https://legiscan.com/CA/text/AB2819/id/1429026.

compliance with the program. Trainings to landlords are taught by law enforcement officers and typically consist of 11 modules given over an 8-hour workshop. Modules cover several topics, which detail the CPTED modifications landlords will need to make to their unit; how to screen tenant applications for a history of criminal justice involvement; how to use and enforce the supplemental lease addendum; and how landlords should communicate with law enforcement (Western Regional Chapter of the International Crime Free Association/Crime Free & Partners, 2009). To maintain compliance with the program, landlords and property managers must attend the training, usually biannually.

Second, after landlords and property managers attend a CFHP training, they must make physical modifications to rental properties to meet CPTED standards. The modifications are intended to deter criminal activity and aid law enforcement during emergencies. The CPTED inspection reports include a comprehensive set of changes to rental units, which include adding "structurally-sound fences in good condition and at a prescribed height;" "lighting throughout parking lot, walks, and pathways;" "posted [CFHP] certificates;" "properly trimmed landscaping;" "deadbolts and eye viewers in units;" "lift and slide protection on windows and sliding doors;" and "removal of graffiti and general cleanliness."

Third, certified properties must include a supplemental lease agreement as part of their lease. ICFA describes the lease agreement as the policy's "heart and soul" (ICFA, n.d.a.). The addenda include language indicating that a resident "shall not engage in any act intended to facilitate criminal activity" and that "a single violation shall be good cause for termination of the lease. Unless otherwise provided by law, proof of violation shall not require criminal conviction, but shall be by a preponderance of the evidence" (City of Fremont, n.d.; City of San Diego, n.d.). Possible violations of the supplemental lease agreement are typically broad and undefined, permitting nearly any interaction with the criminal legal system to serve as justification for an eviction (Archer, 2019; Prochaska, 2023). Violations also do not have to occur on the property, and the behavior of guests or others living in the unit can be the basis for an eviction (Werth, 2013).

Following those three steps, law enforcement agencies certify enrolled buildings as a "crime-free property," which allows landlords and property managers to use the supplemental lease agreement, post a CFHP sign on their property, and mention their certification in advertisements.

CFHPs build on existing efforts to control crime using evictions. As noted by ICFA, CFHPs were inspired by the "war on drugs" policies of the 1970s through 1990s, along with the "one-strike policy," which applies to federally funded public housing (ICFA, n.d.a.; Ramsey Mason, 2018). Accordingly, CFHPs are closely connected to chronic nuisance ordinances, criminal activity nuisance ordinances, and third-party policing strategies (Buerger and Mazerolle, 1998; Prochaska, 2023). These efforts attempt to prevent crime by compelling non-offending third parties to create active guardianship over a given property or face civil penalties. For example, criminal activity nuisance ordinances deem certain activities as nuisances within a municipal statute (using similarly broad language as the supplemental lease agreements used in CFHPs), then subsequently require landlords and property managers to abate nuisances that occur on their property (typically, through evicting the tenant) or face fines and potential loss of rental licenses (Prochaska, 2023).

Limited previous research has been conducted on the impact of those policies on either crime or evictions, although an analysis of criminal activity nuisance ordinances in Ohio found that criminal activity nuisance ordinances increased evictions (Kroeger and La Mattina, 2020). Previous research on criminal activity nuisance ordinances and third-party policing strategies generally have also found that these policies increase evictions among victims of domestic violence (Desmond and Valdez, 2013; Golestani, 2021; Moss and Shastry, 2019). However, CFHPs differ from criminal activity nuisance ordinances because they introduce additional policy components, such as landlord trainings, CPTED modifications, surveillance components, and use of the supplemental lease addenda. Identifying the effect of CFHPs on evictions could provide necessary evidence to local jurisdictions on the potential community costs of implementing such policies.

Data Sources and Variables

At the project's start, the authors were unable to find data sources on evictions in municipalities across California. The state limits access to unlawful detainer court filings due to AB2819, which permits access to records only in narrow circumstances. The few existing available sources on evictions in California either detail filing counts at the county-year level, such as reports by the Judicial Council of California or The Eviction Lab, or report filings for specific geographies in Los Angeles or San Francisco (Gromis et al., 2022; Lens et al., 2020; San Francisco Anti-Displacement Coalition, 2015). Given that CFHPs are implemented at the municipal level with specific rental units certified within a city, those datasets would have been unsuitable for analyzing the effect of CFHPs on evictions.

For those reasons, the authors sought records on writs of execution containing the addresses of completed writs through county sheriff's departments. These records pertain to the last step of the eviction process in California, which occurs only when a landlord has been provided a judgment of possession (which provides landlords the right to evict a tenant following a trial decision), the tenant has been provided a notice to vacate, and the tenant has not moved out after 5 days following the notice to vacate.[4] At that point, landlords can obtain a writ of execution, which permits the landlord to request a sheriff to lock the tenant out of the unit. As such, these records are a conservative estimate of total evictions in the state because they do not include any evictions that would have occurred after a tenant was given a notice to vacate and chose to leave the premises voluntarily before a court case, during court proceedings, or after judgment. These records also reflect some of the most severe outcomes of the eviction process because the data pertain to individuals forcibly removed from their units by law enforcement officers.

The authors obtained the writs of execution records by submitting Public Records Act requests to all 58 counties in California between September 2021 and October 2022, requesting records between January 2017 and January 2021. Additional requests were submitted to 30 municipalities and counties in February 2022 seeking information on CFHP implementation. Responses were received from four locations: the City of Hayward, the City of Fremont, the City of Riverside, and San Diego

[4] For additional clarification: A notice to vacate is provided to the tenant following an unlawful detainer proceeding, unlike a notice to quit, which would have been provided to the tenant before the court filing.

County.[5] More details on the request process and data processing can be found in web appendix A. The request language can be found in web appendix B. Sociodemographic indicators were extracted at the block group level from the American Community Survey 5-Year Data Release for the years 2015 through 2019 (U.S. Census Bureau, 2020). Indicators included total population, population proportions by race and ethnicity, number of renting households, and per capita income.

Research Design

This analysis used a recently developed estimator, spatial first differences (SFD), to estimate the effect of CFHPs on evictions (Druckenmiller and Hsiang, 2018).[6] Described briefly, the SFD approach involves organizing relatively small geographic areas into a series of cross-border comparisons between neighbors and then taking the pairwise difference of all included variables across each border to form a series of first-differenced relationships. Those differences are then included within a regression in which the differenced outcome is regressed on a differenced treatment variable and differenced covariates. The approach can be conceptually likened to a difference-in-differences (two-way fixed effects) estimator, which employs fixed effects for both time and group membership (such as a set of states by year), aiming to mitigate significant sources of unobserved confounding through differencing (Angrist and Krueger, 1999). In the case of SFD, a spatial sequence of neighboring geographies is substituted for the time dimension, and (arbitrary) contiguous collections of spatial neighbors are substituted for group membership.

Models were estimated separately for the municipalities of Fremont, Hayward, Riverside, and the County of San Diego. All models were estimated using data on evictions in 2019 based on writs of execution records from sheriff's departments in those locations. Treatment status was parameterized at the block group level using one of two measures: a binary indicator, indicating if a block group had one or more CFHP-certified rental units, or a continuous variable, indicating the number of CFHP-certified rental units within a block group. The coefficient on treatment status is the estimand of interest, indicating the policy's average treatment on the treated (ATT) effect. The outcome variable was counts of evictions within census block groups. Models used eviction counts rather than eviction rates due to heteroskedasticity detected in the estimated residuals based on the number of renting households.[7] To compensate for this fact, models used counts as the outcome variable and included the rate denominator—number of renting households—as an additional covariate, similar to an offset variable included in a Poisson or negative binomial regression.

[5] For Fremont, Hayward, and Riverside, local law enforcement agencies (e.g., the Fremont Police Department) administer the CFHP policy, whereas the county sheriff's department implements CFHPs in San Diego County.

[6] For interested readers, the authors also estimated treatment effects using ordinary least squares (OLS) for all model specifications and outcome measures discussed in this article. Results from those models are consistent with the estimated effects found using the spatial first difference estimator.

However, OLS models do not include the crucial estimation strategy of differencing, which removes confounding due to spatially correlated (with treatment) unobservable variables. For more technical details on this benefit of the estimation strategy, see Druckenmiller and Hsiang (2018), specifically the section on equations 17 and 18, which discusses how the estimator, by construction, removes these confounders.

[7] More specifically, block groups with a small number of renting households have a larger variance in eviction rates than block groups with many renting households.

The key identifying assumption for the SFD estimator is called the *local conditional independence* assumption. This assumption states that units are conditionally independent with respect to local spatial neighbors (which is like the assumption for time-based first differencing approaches such as difference-in-differences, in which sequential observations in a time series are assumed to be conditionally independent).[8] The assumption was tested by estimating spatial first difference models across different angles of rotation over geographic space, constructing arbitrarily different sets of spatial neighbors over a full 360 degrees of rotation. If the estimated effect of treatment is similar across those map rotations, that evidence supports the local conditional independence assumption being valid. The authors also investigated how the ATT effect changes when including additional adjustment variables within model specifications. If the ATT effect is substantially different when adjustment variables are included, that outcome would not support the validity of the local conditional independence assumption.

To check SFD results by map rotation (and to determine spatial indices generally), an algorithm was used for determining neighboring locations (Druckenmiller and Hsiang, 2018; Tanutama, 2019). This algorithm samples neighboring block group polygons in a west-to-east direction, aiming to maximize the length of consecutive neighbors. Once the algorithm is unable to find an additional neighbor, it selects a new "sampling channel" with respect to the next-longest possible series of neighbors (the groups in the analogy to a two-way fixed-effects estimator described previously). Iterative sampling channels are selected until all polygons have been ordered next to a neighbor. Web appendix C demonstrates the results of this algorithm for three sampling channels and two map angles (0 degrees and 90 degrees) using block groups in the City of Riverside.

Once first differences were obtained for a given map rotation and subsequent index of spatial neighbors, linear regression models were used to estimate ATT effects. The spatial first difference models used two specifications: an unadjusted model, which included only treatment status and the number of renting households as covariates; and a regression-adjusted model, which included the following additional covariates: population proportion White, population proportion Black, population proportion Asian, population proportion Native American, population proportion Hispanic, and per capita income. More formally, the SFD model specifications corresponded to the following equations:

Unadjusted: $\Delta_\phi E_i = \alpha + \lambda\Delta_\phi H_i + \beta\Delta_\phi P_i + \Delta_\phi\varepsilon_i$

Adjusted: $\Delta_\phi E_{i,} = \alpha + \tilde{\lambda}\Delta_\phi H_i + \tilde{\beta}\Delta_\phi P_i + \gamma\Delta_\phi X_i + \Delta_\phi u_i$

where E_i is a count of evictions for block group I, α is a model intercept, H_i is a number of renting households, P_i is either a binary indicator that equals one when a block group has one or more CFHP-certified rental units or a count of the number of CFHP-certified rental units in a block group, Δ_ϕ is the result of first-differencing neighboring block groups using a map rotation angle ϕ, and X_i is the set of included adjustment covariates. Standard errors were estimated using procedures in Conley (1999) to account for spatial autocorrelation, using the R package conleyreg 4.0.5. All regression tables are available in web appendix D.

[8] In other words, it is assumed that the differences in unobserved variables between two neighboring block groups are minimal (i.e., ignorable), more so than unobserved differences between block groups far apart from each other.

Ultimately, estimated treatment effects are comparable across map rotations. Web appendix E provides the distribution of treatment effect estimates across map angles by location and model (i.e., estimates of β in the previous equations). The displayed densities were derived by sampling 10,000 draws from normal distribution with a mean equal to the mean estimated treatment effect and standard deviation equal to the standard deviation of the estimated treatment effect. Sampled draws of beta coefficients were used to obtain a unified effect across model angles, with draws collapsed using Rubin's rules (Rubin, 2004); specifically, draws were ordered across all model angles from smallest to largest. Then, draws were summarized using the mean of those draws and the 2.5th and 97.5th percentiles, which correspond to the results displayed in the figure for the row "Overall Effect" in the exhibits in web appendix E. These results display comparable direction and magnitude in the estimated treatment effects across model angles, providing evidence that the assumption of local conditional independence is being met (web appendix E).

To simplify the presentation of results, percentage change in evictions were calculated across treated block groups based on the unified treatment effect estimate across model angles (web appendix F). For each site (Fremont, Hayward, Riverside, and San Diego County), a counterfactual change in evictions was calculated by subtracting the estimated treatment effect (and estimated treatment effect confidence intervals) from the observed mean of evictions across treated block groups in each location. These values were used to calculate the percentage change based on the observed mean in each location.[9] A summary treatment effect across sites was calculated by summarizing the treatment effect draws across both sites and model angles using Rubin's rules. The same procedure was used to calculate a counterfactual change using the average eviction count across all sites.

Results

Exhibits 1.1 through 1.4 report descriptive statistics for each variable by study site. The first column displays the mean and standard deviation across block groups that do not contain a CFHP-certified rental unit (control groups). The second column displays the same information for block groups with a CFHP-certified rental unit (treatment groups). The last column displays the estimated mean difference in each variable between treated and control groups, along with the confidence intervals for the mean difference.

[9] For example, percentage change = ATT / Mean evictions.

Exhibit 1.1

Descriptive Statistics in Fremont for Block Groups With and Without CFHP-Certified Rental Units

	Blocks Without CFHP-Certified Units	Blocks With CFHP-Certified Units	Mean Difference
Eviction Count	0.34 (0.76)	2.00 (2.26)	1.67 (0.86, 2.46)
Black (Pop %)	3 (4)	4 (3)	1 (– 1, 2)
Asian (Pop %)	59 (18)	56 (17)	– 3 (– 10, 4)
White (Pop %)	26 (13)	22 (11)	– 4 (– 8, 10)
American Indian/ Alaskan Native (Pop %)	0 (1)	1 (1)	0 (0, 1)
Latin/Hispanic (Pop %)	11 (10)	17 (12)	6 (1, 11)
Per Capita Income	$54,932 ($12,453)	$48,385 ($12,013)	– $6,547 (– $11,472,– $1,622)
Rental Units	169.8 (170.9)	481 (288.1)	311.3 (205.1, 417.4)
CFHP-Certified Properties		1.6 (1.0)	
N	86	32	

CFHP = crime-free housing policy. Pop = population.

Sources: Writs of execution data obtained from sheriff's departments; American Community Survey 5-year data, 2019

Exhibit 1.2

Descriptive Statistics in Hayward for Block Groups With and Without CFHP-Certified Rental Units

	Blocks Without CFHP-Certified Units	Blocks With CFHP-Certified Units	Mean Difference
Eviction Count	1.19 (1.93)	4.58 (4.06)	3.39 (1.06, 5.72)
Black (Pop %)	9 (7)	14 (9)	5 (0, 10)
Asian (Pop %)	26 (14)	20 (5)	– 6 (– 10,– 2)
White (Pop %)	37 (13)	38 (50)	1 (– 3, 5)
American Indian/ Alaskan Native (Pop %)	1 (2)	1 (1)	0 (– 1, 1)
Latin/Hispanic (Pop %)	39 (19)	43 (13)	4 (– 4, 13)
Per Capita Income	$35,544 ($14,279)	$32,630 ($8,444)	– $2,914 (– $8,547, $2,718)
Rental Units	226.8 (174.1)	519.6 (341.7)	292.8 (96, 489.5)
CFHP-Certified Properties		1.3 (1.2)	
N	88	12	

CFHP = crime-free housing policy. Pop = population.

Sources: Writs of execution data obtained from sheriff's departments; American Community Survey 5-year data, 2019

Exhibit 1.3

Descriptive Statistics in Riverside for Block Groups With and Without CFHP-Certified Rental Units

	Blocks Without CFHP-Certified Units	Blocks With CFHP-Certified Units	Mean Difference
Eviction Count	1.65 (1.87)	3.88 (3.71)	2.23 (1.33, 3.14)
Black (Pop %)	6 (6)	7 (5)	2 (0, 3)
Asian (Pop %)	7 (8)	6 (7)	– 1 (– 4, 1)
White (Pop %)	61 (16)	56 (13)	– 5 (– 9,– 1)
American Indian/ Alaskan Native (Pop %)	1 (1)	1 (2)	0 (0, 1)
Latin/Hispanic (Pop %)	51 (23)	58 (19)	7 (1, 13)
Per Capita Income	$29,908 ($13,275)	$22,664 ($10,146)	– $7,244 (– $10,511,– $3,977)
Rental Units	153.4 (154.4)	364.6 (194.6)	211.2 (159.4, 263)
CFHP-Certified Properties		1.9 (1.6)	
N	127	74	

CFHP = crime-free housing policy. Pop = population.

Sources: Writs of execution data obtained from sheriff's departments; American Community Survey 5-year data, 2019

Exhibit 1.4

Summary Statistics in San Diego County for Block Groups With and Without CFHP-Certified Rental Units

	Blocks Without CFHP-Certified Units	Blocks With CFHP-Certified Units	Mean Difference
Eviction Count	1.79 (3.27)	2.87 (2.97)	1.08 (0.38, 1.77)
Black (Pop %)	5 (7)	3 (5)	– 2 (– 3,– 1)
Asian (Pop %)	11 (12)	6 (7)	– 5 (– 6,– 3)
White (Pop %)	72 (17)	77 (12)	5 (2, 8)
American Indian/ Alaskan Native (Pop %)	1 (3)	1 (2)	0 (0, 1)
Latin/Hispanic (Pop %)	32 (25)	40 (26)	8 (2, 14)
Per Capita Income	$40,000 ($20,940)	$30,902 ($12,319)	– $9,098 (– $12,059,– $6,137)
Rental Units	293.3 (312.9)	380.8 (256)	87.4 (27.6, 147.2)
CFHP-Certified Properties		1.8 (1.2)	
N	1693	75	

CFHP = crime-free housing policy. Pop = population.

Sources: Writs of execution data obtained from sheriff's departments; American Community Survey 5-year data, 2019

The descriptive results show that Fremont, Hayward, and San Diego County have higher eviction rates in block groups with CFHP-certified rental units (treated units) compared with block groups without CFHP-certified rental units (control units). However, the mean difference of eviction rates between treated and control groups is nonsignificant across all sites. Across all locations, treated units have significantly more rental properties than control units. In Fremont, Riverside, and San Diego County, treated units have significantly lower per capita income than control units

(-$6,547, -$7,244, and -$9,098, respectively). Per capita income is also lower for treated units in Hayward (-$2,914), although the mean difference is nonsignificant. Concerning race and ethnicity, treated units have a significantly larger Latin/Hispanic population proportion than controls in Fremont, Riverside, and San Diego County, whereas treated units in Hayward and Riverside have a significantly larger Black population proportion. The American Indian/Alaskan Native population proportion for treated units is also modest but statistically significantly larger in Fremont, Riverside, and San Diego County.

Exhibits 2.1 through 2.4 display maps of each site. Shading indicates the number of evictions in each block group, and triangles display the relative location of each CFHP-certified rental unit. To maintain privacy, the number of evictions was categorized into broader bins, and the location of CFHP-certified rental units was randomized in each block group.

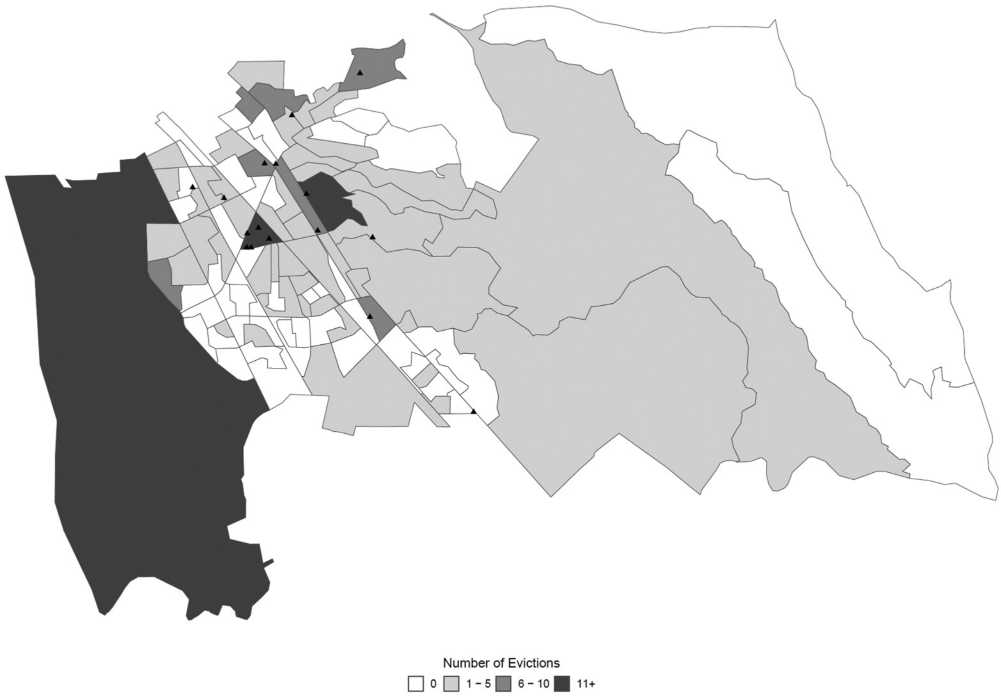
Exhibit 2.1

Number of CFHP-Certified Rental Units and Executed Evictions Within Fremont, California Census Block Groups

Notes: Triangles indicate the relative location of CFHP-certified rental units. The specific location of each rental unit was randomized within block groups.
Source: Public Records Act Requests

Exhibit 2.2

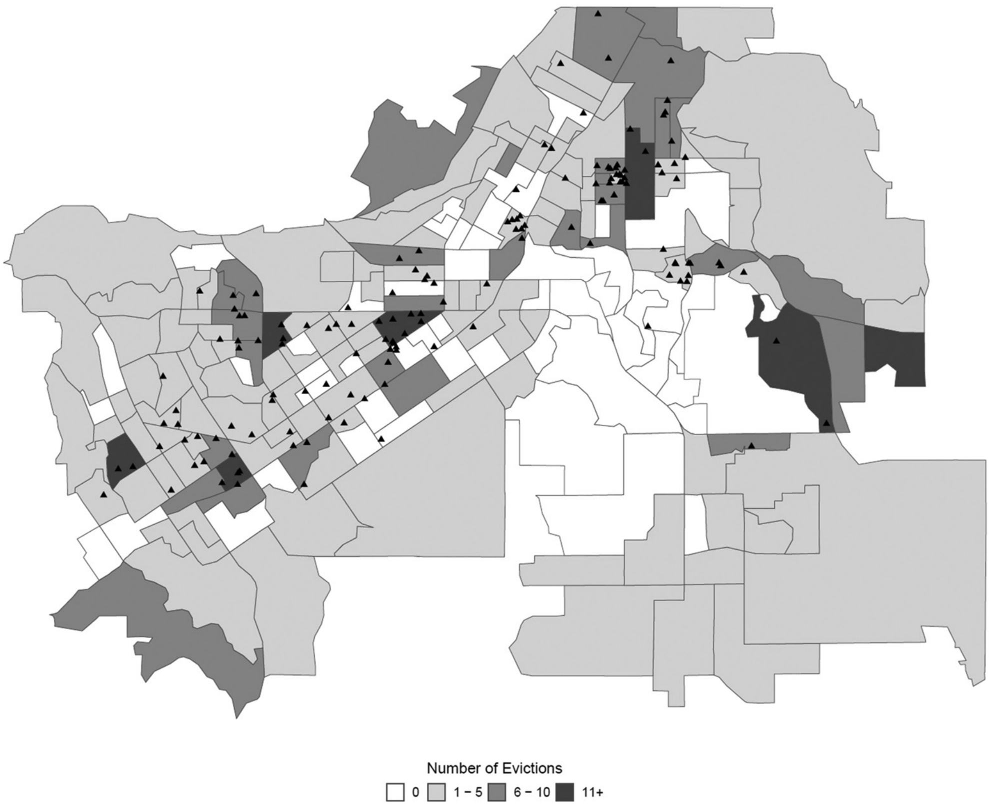
Number of CFHP-Certified Rental Units and Executed Evictions Within Map of Hayward, California Census Block Groups



Notes: Triangles indicate the relative location of CFHP-certified rental units. The specific location of each rental unit was randomized within block groups.
Source: Public Records Act Requests

Exhibit 2.3

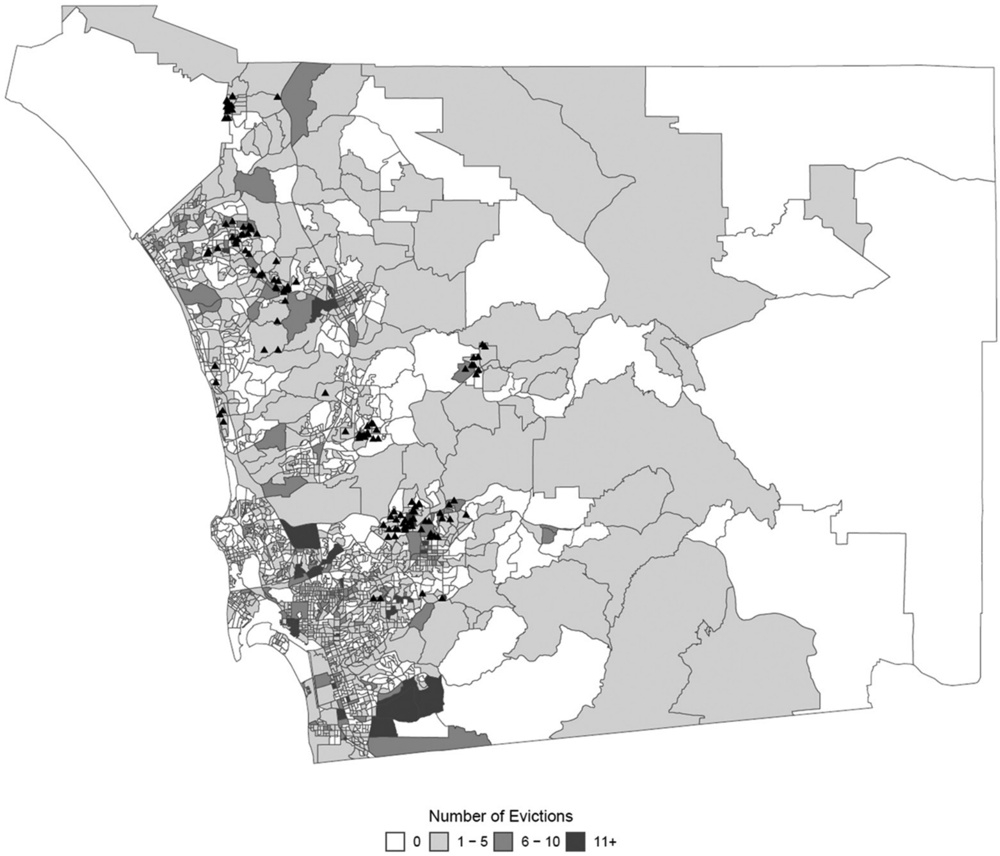
Number of CFHP-Certified Rental Units and Executed Evictions Within Riverside, California Census Block Groups



Notes: Triangles indicate the relative location of CFHP-certified rental units. The specific location of each rental unit was randomized within block groups.
Source: Public Records Act Requests

Exhibit 2.4

Number of CFHP-Certified Rental Units and Executed Evictions Within San Diego County, California Block Groups



Notes: Triangles indicate the relative location of CFHP-certified rental units. The specific location of each rental unit was randomized within block groups.
Source: Public Records Act Requests

The percentage of block groups treated according to the policy varies considerably by location, with 4.2 percent of block groups in San Diego County, 12 percent in Hayward, 27 percent in Fremont, and 37 percent in Riverside. In Fremont and Hayward, treated block groups are clustered within the core of each city. Treated block groups in Riverside are clustered on a west-to-northeast diagonal and within specific cities in San Diego County. The average treated block group contains 1.56 certified properties in Fremont, 1.33 in Hayward, 1.93 in Riverside, and 1.79 in San Diego County.

Empirical Findings

Across all locations, estimated treatment effects are significant, in the same direction, and with comparable magnitude.[10] Regardless of the specific location, model, or treatment measure, treated

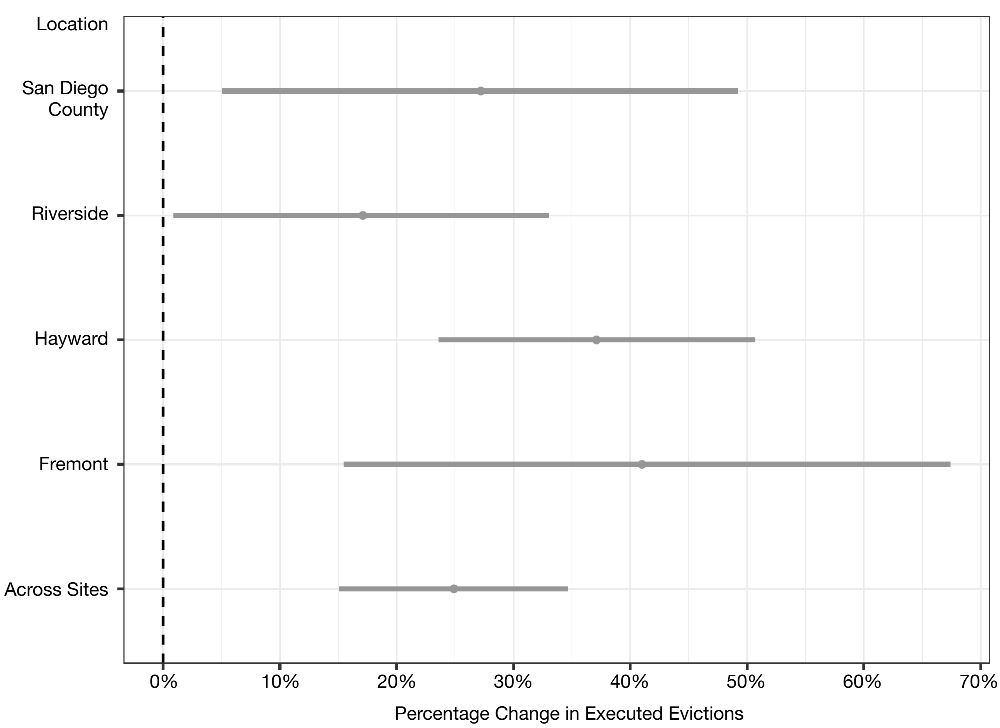
[10] Model regression tables are available in web appendix D, and estimated average treatment-on-the-treated effects by model, location, and site are available in web appendixes E and F.

groups have increased evictions compared with control groups. There is not a large difference in results between the two treatment measures after accounting for the average number of CFHP-certified rental units in treated block groups. In addition, the estimated treatment effects in the adjusted models are similar to the results for unadjusted models, providing additional evidence that the local conditional independence assumption is being met.

Exhibit 3 displays the estimated counterfactual percent change in evictions that occurs in block groups containing one or more CFHP-certified rental properties, using the unadjusted model specification. A significant effect on evictions is found across all locations, with CFHPs increasing evictions within treated block groups by 17.1 percent (0.9 percent, 33 percent) in Riverside; 27.2 percent (5.1 percent, 49.2 percent) in San Diego County; 37.1 percent (23.6 percent, 50.7 percent) in Hayward; and 41 percent (15.5 percent, 67.4 percent) in Fremont. Aggregating the effect across sites, treated block groups experience a 24.9 percent (15.1 percent, 34.6 percent) increase in evictions.

Exhibit 3

Estimated Percentage Change in Evictions in Block Groups Containing CFHP-Certified Rental Units, by Location



Source: Authors calculations using results from Spatial First Difference Models

Conclusion

This analysis demonstrates that crime-free housing policies (CFHPs) increase the number of evictions that occur in neighborhood blocks by an average of 24.9 percent. Evictions are a harmful outcome for individuals and carry a large social cost to governments and communities. Policymakers considering instating policies that rely on evictions to generate an outcome, including third-party policing efforts such as CFHPs, should carefully weigh the costs of additional evictions against the policy's purported benefit. The effect on evictions identified in this study may be similar for other policies—including criminal activity nuisance ordinances, chronic nuisance ordinances, and the one-strike policy—that use evictions based on nuisance actions and contact with the criminal justice system as a strategy to prevent crime. For example, previous research investigating the effect of criminal nuisance ordinances in Ohio found that such policies increased eviction filings by 16 percent (Kroeger and La Mattina, 2020). The close similarity in enforcement strategies across these policies, which differ mainly in the source of statutory language enabling the enforcement (i.e., as either a municipal ordinance or as a supplemental lease agreement), suggests that these policy efforts may have similar effects on evictions.

U.S. Department of Housing and Urban Development memos have raised additional concerns about the implementation of CFHPs (Kanovsky, 2016; McCain, 2022). Those memos focused on how CFHPs could cause a disproportionate number of evictions for victims of domestic violence and cautioned municipalities that CFHPs may cause discrimination in housing access because they prevent formerly incarcerated individuals from tenancy. However, fewer concerns have been raised about the effect of CFHPs on evictions generally. Given the population harm of evictions, municipalities must weigh the costs and benefits of maintaining CFHPs because, even if the policy achieves the stated aim of crime reduction, it may introduce additional community harms. However, recent evidence has found that CFHPs likely do not decrease crime rates, and analysis on nuisance ordinances has shown that they may, in fact, increase crime (Falcone, 2023; Griswold et al., 2023). Evictions may also lead to additional crime, undermining the purpose of CFHPs (Semenza et al., 2022). Further, as the descriptive statistics demonstrate, lower-income populations are disproportionately affected by CFHPs. Eviction events can create disproportionate harm for low-income individuals because evictions can lead to increased financial losses, additional housing instability due to the eviction record, challenges in obtaining subsidized housing, and increased risk of homelessness events (Collinson et al., 2023; Desmond, Gershenson, and Kiviat, 2015; Desmond and Shollenberger, 2015).

One justification offered for the use of third-party policing strategies, such as CFHPs, is that they are cost-effective, reducing the need to use law enforcement resources to prevent crime by promoting landlords to engage in active guardianship over their rental units (Buerger and Mazerolle, 1998; Mazerolle and Roehl, 1998). However, this analysis shows that CFHPs increase the number of completed writs of execution, which would subsequently increase the cost of administering the policy. Each completed writ requires law enforcement resources to execute it, suggesting that CFHPs could increase overall net resource use with little benefit on crime. CFHPs may also lead to other costs to the public as well. Previous evidence suggests that each eviction has a lower bound cost of $8,000 per person evicted, not including court or law enforcement costs associated with executing an eviction (Collinson and Reed, 2018). As such, CFHPs may carry a large cost burden for municipalities that implement the policy, given the magnitude of the identified effect on evictions.

The results also indicate that blocks with CFHP-certified rental units contain more renters, have a lower per capita income, and, depending on the exact location, a larger proportion of Black and Latin/Hispanic populations than blocks without CFHP-certified rental units. By increasing the number of evictions in those blocks, CFHPs may further marginalize low-income populations and people of color and may increase housing instability, homelessness, and the use of social services among those populations.

CFHPs' targets for enforcement are renters in multifamily housing units and individuals with a history of criminal justice involvement. Those populations tend to be more non-White and have lower income than the general population, indicating that CFHPs may have a further disproportionate effect on low-income Black and Latin/Hispanic populations, in addition to the demographic difference of the affected neighborhoods displayed in exhibits 1.1 through 1.4 (DeSilver, 2021; Zeng, 2022). Eviction events also disproportionately affect Black women and children, which further increases the potential risk of discrimination occurring from the use of CFHPs (Graetz et al., 2023; Hepburn, Louis, and Desmond, 2020). Previous research has also noted that the populations enforcing CFHPs—law enforcement officers and landlords—may make racially discriminatory choices when provided additional discretion in their decisionmaking (Archer, 2019; Christensen, Sarmiento-Barbieri, and Timmins, 2021; Goff et al., 2016; Hanson and Hawley, 2011; Lofstrom et al., 2022).

In addition to the populations affected by CFHPs, policymakers and government prosecutors have noted that CFHPs may have a discriminatory impact due to the policy's enforcement. For example, the Department of Justice pursued a lawsuit against the City of Hesperia, California, alleging that the city adopted a CFHP to discriminate against Black and Latin/Hispanic individuals in the municipality (U.S. Department of Justice, 2022). In addition, California recently passed a new law, AB1418, to curtail the use of CFHPs in California municipalities.[11] As part of the bill's committee summary, legislators noted that the introduction of the bill was motivated by the potential of CFHPs to produce racially segregative effects and discriminatory impacts.[12]

Legal researchers have noted additional harms that may result from continued use of CFHPs and related policies—beyond the harms caused by additional evictions and potential discriminatory effects. For instance, legal researchers have argued that the application of CFHPs could lead to violations of the Fair Housing Act; First Amendment rights, such as freedom of association; and Fourteenth Amendment rights, such as procedural due process and equal protection (Jarwala and Singh, 2019; Katach, 2015; Prochaska, 2023; Ramsey Mason, 2018; Smith, 2018; Werth, 2013). Policymakers should consider those additional possible harms—in addition to the results concerning CFHPs' effect on evictions and the demographics of affected populations—when considering continued use or adoption of crime-free housing policies.

[11] CA AB1418, 2023–2024 Regular Session, Amended April 12, 2023. https://legiscan.com/CA/text/AB1418/id/2778119.

[12] Assembly Committee on Judiciary. "Tenancy: Local Regulations: Contact With Law Enforcement or Criminal Convictions." Date of Hearing: April 11, 2023. https://trackbill.com/s3/bills/CA/2023/AB/1418/analyses/assembly-judiciary.pdf.

Limitations

This study carries limitations. First, the data collected on evictions is based on writs of execution records, which are issued only to tenants who have lost an unlawful detainer case and have not vacated their unit. Accordingly, the estimated effect using these data may not hold for informal, illegal, or eviction filings if the pattern in those measures differs considerably between treated and control units compared with the writs data. For example, if landlords of CFHP-certified properties use the serial threat of evictions to remove tenants from their housing more often than landlords without CFHP certification and more often than using writs, then the estimates could understate the true effect on evictions. Writs of execution records are also an underestimate of the total number of evictions that occur in neighborhood blocks because the records apply only to tenants forcibly removed from their rental unit. Accordingly, the estimated effect of CFHPs on completed evictions (as measured by writs of execution) is likely an underestimate of the effect of CFHPs on evictions generally.

Second, while processing the writs of execution records, multiple observations had to be removed from the dataset due to incomplete address and date information, retractions, and implausible geocodes. If the records removed from the analysis are not randomly distributed across treated units and control units, this fact may bias the estimated effect.

Third, if the local conditional independence assumption for spatial first differences does not hold, then the estimated average treatment effects might be biased. This assumption was tested using available evidence from map rotations and adjusted models, with results suggesting the assumption may be valid. However, if a confounding variable exists that is not removed from the analysis through the spatial differencing strategy, then the assumption may not hold, and the estimates may not reflect an unbiased causal relationship.

Summary

Crime-free housing policies (CFHPs) significantly increase the number of evictions that occur in neighborhood blocks containing CFHP-certified rental units. Affected neighborhood blocks tend to have lower per capita income, a larger proportion of Black and Latin/Hispanic populations, and more rental units than the broader municipality. Given the substantial harm of evictions and the cost of evictions for local governments, municipalities should weigh the cost and benefits of maintaining or adopting policies that use eviction to achieve a policy outcome.

In addition, CFHPs are closely related to criminal activity nuisance ordinances, chronic nuisance ordinances, and the one-strike policy, which are widely prevalent across the United States and employ a similar enforcement strategy: using evictions as a crime prevention tool. Those policies also likely increase the number of evictions that occur in the United States. Emerging evidence also suggests that those policies likely do not lead to a reduction in crime, indicating that no concomitant benefit stems from increased evictions. On the basis of those findings, federal and state legislators should closely evaluate the efficacy of using evictions to prevent crime and determine if new legislation is needed to curtail the harmful effects of those policies on communities.

Appendix A. Additional Method Details

Data Processing

Data were received from 55 sheriff's departments in California as either physical documents, Excel files, or PDFs. In total, 14,082 pages of records were received and six Excel files. Appendix G provides a synthetic example of a record page. Physical documents were scanned, converted into PDFs using optical character recognition, and post-processed to make records uniform before data extraction. To do so, hand-scanned documents were rotated so that text was aligned horizontally, identified retractions in documents and replaced them with white blocks, and replaced all other colors with black. Post-processing was performed in Python 3.8.

For files received as PDFs or converted into PDFs, the Azure-AI-Form Recognizer 3.2.0 was used to train eight custom template extraction models to generate tabular data from the PDF files. To train the models, 40 pages of records were hand coded, corresponding to the eight main templating formats received across jurisdictions. Those codes indicated the position of rows and columns within each templating format. The accuracy of the extracted tables was validated by calculating the Levenshtein distance ratio between text in PDFs and extracted tables, finding that the distance ratio exceeded 0.98 across all template formats, indicating a high degree of alignment between extracted text and underlying documents. The final generated dataset consisted of rows for completed writs of execution, along with the event's data and address.

Before post-processing, the dataset consisted of 244,298 records. The following rows were removed from the analysis dataset: rows that did not contain date or location information; contained NA values due to a retraction (departments confirmed that retractions pertained to canceled writs); contained a malformed date due to how the document had been scanned by the sheriff's office; was a duplicate record; or corresponded to a scheduled or canceled writ (rather than a completed writ). Addresses were geocoded to GPS coordinates using the Tidygeocoder package in R 4.2.2. (Cambon et al., 2021). Coordinates were validated by comparing imputed ZIP Codes from geocoding to existing ZIP Codes in the original address text. Across all locations, ZIP Codes were successfully matched for 98 percent of imputed addresses. Rows that did not have imputed ZIP Codes that matched address text were inspected, where these rows contained either informal address text (e.g., "Apartment behind the McDonald's on 96th St.") or address text with incomplete information due to hand scanning; these rows were subsequently removed from the analysis dataset. Finally, geocoded addresses were merged with 2019 Census TIGER files and aggregated eviction counts to the block group level. The final analysis dataset contained 216,412 records.

Descriptive Statistics

The mean and standard deviation was calculated for each included study variable within each location in the spatial first difference models (Fremont, Hayward, Riverside, and San Diego County). Means and standard deviations were stratified by treatment status between block groups containing CFHP-certified rental units and block groups without CFHP-certified rental units (exhibits 1.1–1.3). The mean difference between "Blocks With CFHP-Certified Units" and "Blocks Without CFHP-Certified Units," was calculated, along with the confidence interval for the mean difference, based on an unpaired t-test with unequal variance (Welch's t-test). The 95-percent confidence interval of the t-test for the mean difference is provided to categorize the uncertainty. A confidence interval of the mean difference that crosses zero indicates that the mean difference is nonsignificant at the 5-percent threshold.

Appendix B. Public Records Act Requests

Exhibit B.1

Public Records Act Request: Writs of Execution

Hello,

This is a request under the California Public Records Act (pursuant to California Government Code Section 6253(c)) for records in the possession of the [sheriff department name] pertaining to notices of restoration (e.g. completed evictions) given between Jan 1st, 2017 through Jan 1st, 2021. This information should include:

Records or lists of evictions showing served Notice of Restoration, including the following pieces of information:

- The date the notice of restoration was served, including month & year.
- The city in which the notice of restoration was served.

Thanks to the department for the work on responding to this request.

Kind regards,

Exhibit B.2

Public Records Act Request: CFHP Information

Hello,

This is a request under the California Public Records Act (pursuant to California Government Code Section 6253(c)). We are seeking records on [city's name] "Crime-Free Housing Program". Specifically, we are looking for the following pieces of information:

- In what month/year was the program adopted by the city?
- If the program was in place during 2019, what properties were certified under the program (specifically, we are seeking a list with the addresses for these properties)?
- If the program had been implemented in 2019, could the city provide the training documentation and lease addendum used by the program?
- If the program had been implemented in 2019, could the city provide any electronic databases or text databases related to the enforcement of this program?

Thanks to the city for the work on responding to this request.

Kind regards,

Exhibit B.3

CPRA Request: CFHP Information with Additional Details

Hello,

This is a request under the California Public Records Act (pursuant to California Government Code Section 6253(c)). We are seeking records on [city's name] "Crime-Free Housing Program". Specifically, we are looking for the following pieces of information:

- In what month/year was the program adopted by the city?

We additionally are requesting materials related to the operation of the county's crime-free housing program, specifically:

- Documents concerning properties eligible for crime-free housing program enforcement or violations, including the address of properties participating in the program.
- All documents concerning the crime-free housing program, including enforcement of it against residential properties, landlords, or tenants, including copies of all violations, letters, notices, files, and any other external or internal communication, including emails, related thereto since the program's formation to the present.
- Documents that describe policies or procedures for the writing of police and/or incident reports by the sheriff's department when there is a violation of the crime-free housing program.
- Electronic copy of any database or databases containing information regarding the crime-free housing program's enforcement.
- Police and/or incident reports corresponding to violations of the crime-free housing program.
- All training or informational materials regarding the crime-free housing program provided to landlords, tenants, police, or others, including any electronic, video, or audio recordings of trainings.
- All documents concerning mandatory or suggested lease terms or crime-free lease addendum promoted, adopted, or created by the department.
- Any internal or external communications with elected officials or city employees regarding the crime-free housing program since the program's adoption.

Thanks to the city for the work on responding to this request.

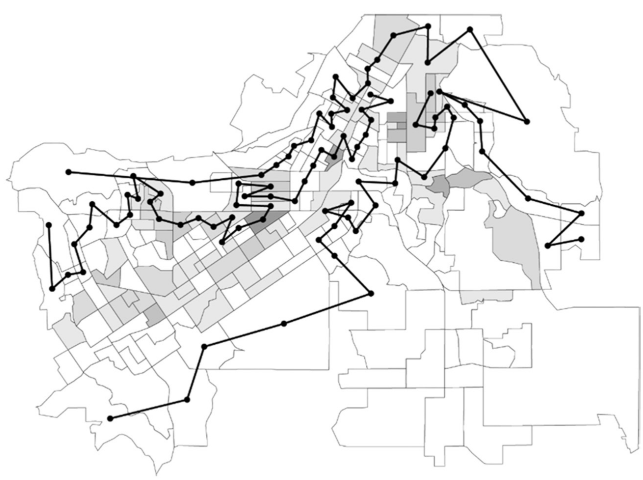
Kind regards,

Appendix C. Example of Sampling Algorithm

Exhibit C.1

Example of Sampling Algorithm Used to Determine Neighboring Block Groups in the City of Riverside When the Map is Rotated Zero and 90 Degrees (1 of 2)

0°

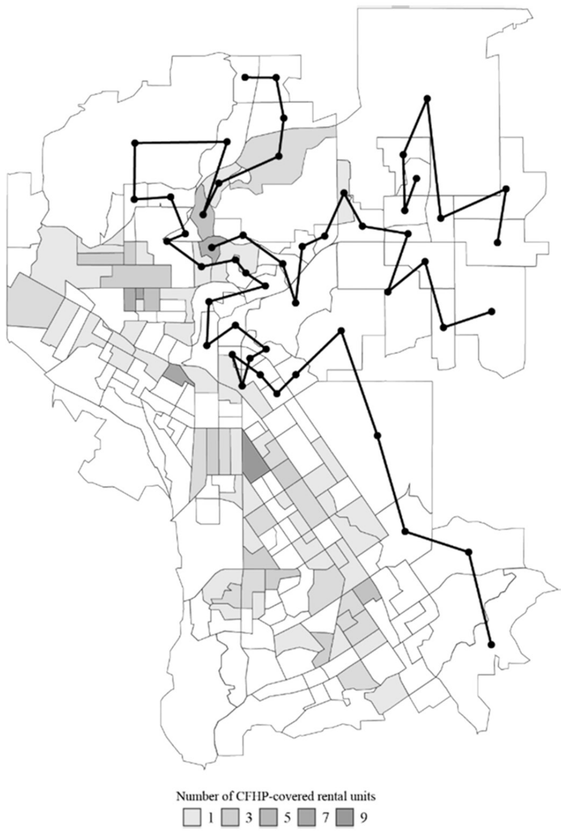


Source: Authors

Exhibit C.1

Example of Sampling Algorithm Used to Determine Neighboring Block Groups in the City of Riverside When the Map is Rotated Zero and 90 Degrees (2 of 2)

90°



Source: Authors

Appendix D. Regression Results for Spatial First Differences Models

Exhibit D.1

Regression Results by Map Rotation for Fremont, Unadjusted Spatial First Differences Model Using Binary Treatment

	Angle=0	Angle=30	Angle=60	Angle=90	Angle=120	Angle=150	Angle=180	Angle=210	Angle=240	Angle=270	Angle=300
One or More CFHP Units	1.09* (0.07)	1.11* (0.07)	0.86* (0.06)	0.31* (0.03)	0.78* (0.06)	1.14* (0.07)	0.55* (0.05)	0.81* (0.06)	0.86* (0.07)	0.95* (0.06)	1.16* (0.07)
Rental Units (in hundreds)	0.18* (0.01)	0.17* (0.01)	0.11* (0.01)	0.19* (0.01)	0.19* (0.01)	0.11* (0.01)	0.18* (0.01)	0.24* (0.01)	0.14* (0.01)	0.14* (0.01)	0.15* (0.01)
Treated Units	32	32	32	32	32	32	32	32	32	32	32
Total Units	103	102	106	103	106	105	106	105	105	104	102
Adjusted R-Squared	0.26	0.26	0.14	0.16	0.19	0.18	0.16	0.23	0.16	0.19	0.26

* $p < 0.05$.

CFHP = crime-free housing policy.

Exhibit D.2

Regression Results by Map Rotation for Hayward, Unadjusted Spatial First Differences Model Using Binary Treatment

	Angle=0	Angle=30	Angle=60	Angle=90	Angle=120	Angle=150	Angle=180	Angle=210	Angle=240	Angle=270	Angle=300
One or More CFHP Units	1.64* (0.09)	1.65* (0.09)	1.65* (0.11)	2.01* (0.09)	1.88* (0.10)	1.89* (0.10)	1.87* (0.10)	1.82* (0.10)	1.19* (0.09)	1.26* (0.11)	2.01* (0.09)
Rental Units (in hundreds)	0.52* (0.02)	0.51* (0.02)	0.55* (0.01)	0.51* (0.02)	0.53* (0.02)	0.53* (0.02)	0.54* (0.02)	0.62* (0.01)	0.55* (0.02)	0.56* (0.02)	0.58* (0.01)
Treated Units	12	12	12	12	12	12	12	12	12	12	12
Total Units	88	88	89	87	92	92	92	90	92	92	87
Adjusted R-Squared	0.35	0.34	0.36	0.36	0.3	0.3	0.3	0.36	0.29	0.3	0.41

* $p < 0.05$.

CFHP = crime-free housing policy.

Source: Authors

Exhibit D.3

Regression Results by Map Rotation for Riverside, Unadjusted Spatial First Differences Model Using Binary Treatment

	Angle=0	Angle=30	Angle=60	Angle=90	Angle=120	Angle=150	Angle=180	Angle=210	Angle=240	Angle=270	Angle=300
One or More CFHP Units	0.29* (0.09)	0.30* (0.10)	0.18 (0.10)	0.52* (0.11)	0.28* (0.10)	0.72* (0.09)	0.69* (0.07)	0.49* (0.09)	1.13* (0.13)	0.97* (0.14)	0.47* (0.11)
Rental Units (in hundreds)	0.84* (0.02)	0.82* (0.02)	0.85* (0.03)	0.80* (0.03)	0.78* (0.02)	0.69* (0.02)	0.64* (0.02)	0.64* (0.02)	0.64* (0.02)	0.70* (0.03)	0.74* (0.03)
Treated Units	74	74	74	74	74	74	74	74	74	74	74
Total Units	178	177	175	179	185	185	183	182	181	181	182
Adjusted R-Squared	0.38	0.37	0.38	0.37	0.34	0.31	0.27	0.27	0.3	0.34	0.33

** $p < 0.05$.*

CFHP = crime-free housing policy.

Exhibit D.4

Regression Results by Map Rotation for Fremont, Unadjusted Spatial First Differences Model Using Binary Treatment

	Angle=0	Angle=30	Angle=60	Angle=90	Angle=120	Angle=150	Angle=180	Angle=210	Angle=240	Angle=270	Angle=300
One or More CFHP Units	0.51* (0.17)	0.67* (0.19)	1.01* (0.25)	0.72* (0.21)	1.45* (0.38)	0.54* (0.17)	0.68* (0.25)	0.69* (0.23)	0.93* (0.28)	0.80* (0.20)	1.00* (0.13)
Rental Units (in hundreds)	0.43* (0.07)	0.50* (0.09)	0.40* (0.10)	0.40* (0.10)	0.39* (0.10)	0.41* (0.11)	0.50* (0.09)	0.40* (0.11)	0.37* (0.10)	0.36* (0.10)	0.32* (0.09)
Treated Units	75	75	75	75	75	75	75	75	75	75	75
Total Units	1,590	1,582	1,580	1,579	1,592	1,616	1,611	1,612	1,614	1,593	1,589
Adjusted R-Squared	0.18	0.22	0.17	0.17	0.17	0.17	0.22	0.18	0.17	0.14	0.14

** $p < 0.05$.*

CFHP = crime-free housing policy.

Source: Authors

Exhibit D.5

Regression Results by Map Rotation for Fremont, Adjusted Spatial First Differences Model Using Binary Treatment

	Angle=0	Angle=30	Angle=60	Angle=90	Angle=120	Angle=150	Angle=180	Angle=210	Angle=240	Angle=270	Angle=300
One or More CFHP Units	1.00* (0.07)	1.08* (0.06)	0.79* (0.06)	0.20* (0.03)	0.76* (0.06)	0.98* (0.06)	0.47* (0.04)	0.79* (0.06)	0.83* (0.06)	0.85* (0.06)	1.18* (0.07)
Rental Units (in hundreds)	0.18* (0.01)	0.16* (0.01)	0.12* (0.01)	0.21* (0.01)	0.18* (0.01)	0.08* (0.01)	0.20* (0.01)	0.23* (0.01)	0.14* (0.01)	0.12* (0.01)	0.14* (0.01)
Per Capita Income (in $10,000)	– 0.10 (0.02)	– 0.08* (0.02)	0.01 (0.02)	0.00 (0.02)	– 0.10* (0.02)	– 0.23* (0.04)	– 0.05 (0.03)	– 0.08* (0.03)	– 0.10 (0.02)	– 0.10* (0.02)	– 0.08* (0.02)
Asian (Pop %)	0.27 (0.31)	0.23 (0.28)	– 2.30* (0.37)	– 0.15 (0.17)	– 0.95* (0.45)	0.58 (0.32)	– 1.02* (0.32)	– 2.05* (0.43)	– 0.17 (0.31)	– 0.49 (0.28)	0.23 (0.27)
White (Pop %)	5.09* (0.68)	4.84* (0.66)	0.41 (0.71)	3.68* (0.45)	1.51* (0.54)	4.33* (0.55)	– 0.02 (0.35)	1.63* (0.81)	3.82* (0.61)	5.49* (0.53)	4.93* (0.58)
Black (Pop %)	1.07* (0.27)	0.95* (0.24)	– 1.48* (0.37)	1.98* (0.19)	– 0.36 (0.37)	0.73* (0.25)	– 0.06 (0.24)	– 1.33* (0.33)	0.59* (0.24)	– 0.34 (0.25)	1.24* (0.25)
American Indian/ Alaska Native (Pop %)	24.38* (1.97)	27.49* (1.67)	13.47* (1.76)	27.34* (2.33)	21.56* (1.67)	27.21* (1.68)	25.04* (1.84)	28.10* (3.00)	27.07* (2.44)	27.44* (2.11)	21.49* (1.69)
Latin/Hispanic (Pop %)	– 1.58* (0.39)	– 1.78* (0.38)	– 2.63* (0.43)	– 2.54* (0.19)	– 3.98* (0.41)	– 0.68* (0.32)	– 1.99* (0.29)	– 5.65* (0.59)	– 1.89* (0.37)	– 2.29* (0.32)	– 3.02* (0.32)
Treated Units	32	32	32	32	32	32	32	32	32	32	32
Total Units	103	102	106	103	106	105	106	105	105	104	102
Adjusted R-Squared	0.26	0.26	0.1	0.19	0.2	0.18	0.15	0.26	0.16	0.2	0.27

** $p < 0.05$.*

CFHP = crime-free housing policy. Pop = population.

Source: Authors

Exhibit D.6

Regression Results by Map Rotation for Hayward, Adjusted Spatial First Differences Model Using Binary Treatment

	Angle=0	Angle=30	Angle=60	Angle=90	Angle=120	Angle=150	Angle=180	Angle=210	Angle=240	Angle=270	Angle=300
One or More CFHP Units	1.53* (0.09)	1.55* (0.09)	1.70* (0.12)	1.99* (0.11)	2.04* (0.11)	2.05* (0.11)	2.02* (0.12)	1.65* (0.12)	1.22* (0.09)	1.20* (0.11)	1.97* (0.10)
Rental Units (in hundreds)	0.63* (0.02)	0.62* (0.02)	0.62* (0.02)	0.54* (0.03)	0.57* (0.02)	0.57* (0.02)	0.60* (0.02)	0.71* (0.02)	0.63* (0.02)	0.64* (0.02)	0.68* (0.02)
Per Capita Income (in $10,000)	0.21* (0.03)	0.28* (0.03)	0.18* (0.03)	0.17* (0.03)	0.44* (0.07)	0.45* (0.07)	0.50* (0.07)	0.78* (0.07)	0.39* (0.06)	0.35* (0.06)	0.13* (0.04)
Asian (Pop %)	– 4.97* (0.40)	– 4.58* (0.45)	– 3.80* (0.46)	– 3.40* (0.52)	– 4.94* (0.62)	– 5.05* (0.63)	– 4.38* (0.65)	– 4.08* (0.59)	– 2.56* (0.64)	– 4.19* (0.51)	– 2.26* (0.50)
White (Pop %)	– 5.83* (0.66)	– 5.12* (0.58)	– 7.88* (0.65)	– 4.00* (0.49)	– 7.02* (0.39)	– 7.19* (0.40)	– 5.64* (0.39)	– 6.40* (0.42)	– 9.08* (0.46)	– 8.99* (0.56)	– 5.75* (0.58)
Black (Pop %)	– 5.15* (0.41)	– 4.75* (0.39)	– 5.15* (0.47)	– 4.03* (0.43)	– 5.47* (0.45)	– 5.49* (0.46)	– 4.37* (0.43)	– 4.63* (0.43)	– 5.47* (0.36)	– 6.50* (0.42)	– 4.60* (0.42)
American Indian/ Alaskan Native (Pop %)	15.32* (1.38)	15.33* (1.38)	5.50* (0.95)	– 4.59* (1.13)	– 11.82* (2.03)	– 12.14* (2.00)	– 8.01* (2.05)	– 16.31* (3.23)	6.18* (1.99)	6.49* (1.99)	5.75* (1.33)
Latin/Hispanic (Pop %)	– 5.01* (0.35)	– 4.55* (0.33)	– 4.89* (0.41)	– 3.68* (0.41)	– 3.87* (0.42)	– 3.95* (0.43)	– 3.77* (0.45)	– 3.48* (0.35)	– 1.92* (0.31)	– 3.33* (0.29)	– 3.96* (0.39)
Treated Units	12	12	12	12	12	12	12	12	12	12	12
Total Units	88	88	89	87	92	92	92	90	92	92	87
Adjusted R-Squared	0.38	0.39	0.4	0.36	0.32	0.33	0.32	0.42	0.33	0.34	0.44

** $p < 0.05$.*

CFHP = crime-free housing policy. Pop = population.

Source: Authors

Exhibit D.7

Regression Results by Map Rotation for Riverside, Adjusted Spatial First Differences Model Using Binary Treatment

	Angle=0	Angle=30	Angle=60	Angle=90	Angle=120	Angle=150	Angle=180	Angle=210	Angle=240	Angle=270	Angle=300
One or More CFHP units	0.35* (0.09)	0.34* (0.11)	0.21* (0.11)	0.67* (0.12)	0.39* (0.10)	0.80* (0.09)	0.88* (0.06)	0.65* (0.09)	1.21* (0.12)	1.16* (0.13)	0.65* (0.11)
Rental Units (in hundreds)	0.88* (0.02)	0.88* (0.03)	0.90* (0.03)	0.83* (0.03)	0.83* (0.02)	0.72* (0.02)	0.61* (0.02)	0.62* (0.03)	0.66* (0.02)	0.67* (0.03)	0.73* (0.03)
Per Capita Income (in $10,000)	0.19* (0.02)	0.26* (0.02)	0.26* (0.02)	0.24* (0.02)	0.36* (0.02)	0.23* (0.03)	0.18* (0.02)	0.13* (0.03)	0.14* (0.04)	0.24* (0.03)	0.11* (0.03)
Asian (Pop %)	0.50 (0.57)	– 5.30* (0.89)	– 4.83* (0.93)	– 3.33* (1.08)	1.82 (1.20)	2.21 (1.20)	4.75* (1.16)	6.89* (1.01)	6.24* (1.11)	5.93* (0.63)	2.18* (0.51)
White (Pop %)	– 6.37* (0.36)	– 8.84* (0.59)	– 8.18* (0.65)	– 8.50* (0.60)	– 6.26* (0.70)	– 4.35* (0.85)	0.42 (0.61)	– 1.09 (0.81)	– 2.79* (0.88)	– 2.08* (0.59)	– 2.77* (0.54)
Black (Pop %)	– 3.19* (0.20)	– 3.50* (0.27)	– 3.13* (0.29)	– 3.88* (0.26)	– 1.73* (0.29)	– 2.85* (0.31)	– 2.17* (0.26)	– 1.54* (0.24)	– 2.02* (0.32)	– 2.48* (0.24)	– 2.36* (0.17)
American Indian/ Alaskan Native (Pop %)	9.39* (2.01)	9.21* (2.25)	8.26* (2.30)	5.07* (2.31)	4.43* (1.85)	0.88 (1.71)	14.68* (1.74)	9.93* (1.73)	8.42* (2.08)	4.67* (1.99)	7.38* (2.40)
Latin/Hispanic (Pop %)	1.44* (0.31)	– 0.42* (0.18)	– 0.11 (0.20)	0.69* (0.22)	1.07* (0.22)	0.50* (0.24)	2.31* (0.19)	1.95* (0.25)	1.10* (0.34)	2.18* (0.27)	2.37* (0.25)
Treated Units	74	74	74	74	74	74	74	74	74	74	74
Total Units	178	177	175	179	185	185	183	182	181	181	182
Adjusted R-Squared	0.42	0.39	0.39	0.39	0.36	0.32	0.31	0.3	0.32	0.36	0.37

** $p < 0.05$.*

CFHP = crime-free housing policy. Pop = population.

Source: Authors

Exhibit D.8

Regression Results by Map Rotation for San Diego County, Adjusted Spatial First Differences Model Using Binary Treatment

	Angle=0	Angle=30	Angle=60	Angle=90	Angle=120	Angle=150	Angle=180	Angle=210	Angle=240	Angle=270	Angle=300
One or More CFHP Units	0.42* (0.16)	0.57* (0.18)	1.03* (0.24)	0.73* (0.19)	1.41* (0.35)	0.57* (0.17)	0.76* (0.23)	0.70* (0.21)	0.85* (0.25)	0.71* (0.17)	0.84* (0.11)
Rental Units (in hundreds)	0.41* (0.07)	0.48* (0.09)	0.39* (0.10)	0.39* (0.10)	0.38* (0.10)	0.40* (0.11)	0.50* (0.09)	0.39* (0.11)	0.36* (0.11)	0.34* (0.11)	0.30* (0.09)
Per Capita Income (in $10,000)	0.01 (0.03)	0.02 (0.03)	0.03 (0.05)	0.07 (0.05)	0.00 (0.03)	0.05 (0.04)	0.18* (0.04)	0.07 (0.04)	0.03 (0.03)	– 0.04 (0.03)	– 0.12* (0.03)
Asian (Pop %)	1.64* (0.37)	1.06* (0.29)	1.22* (0.58)	1.74* (0.67)	0.61 (0.58)	1.04 (0.94)	0.35 (0.69)	0.99 (0.84)	– 0.18 (0.79)	0.26 (0.89)	1.68* (0.40)
White (Pop %)	3.24* (0.54)	2.89* (0.41)	4.53* (0.85)	5.28* (1.16)	1.62 (1.32)	2.60* (1.20)	2.75* (1.02)	3.89* (1.22)	1.48 (1.08)	2.14* (1.07)	2.21* (0.67)
Black (Pop %)	– 0.18 (0.35)	– 0.43* (0.21)	– 0.40 (0.45)	– 0.09 (0.47)	– 1.13* (0.50)	– 1.59* (0.59)	– 0.80 (0.59)	0.12 (0.71)	– 1.13 (0.61)	– 0.87 (0.65)	0.29 (0.25)
American Indian/ Alaskan Native (Pop %)	0.69 (1.01)	– 1.13 (0.77)	– 2.61* (0.82)	– 2.29* (0.66)	– 4.20* (0.79)	– 4.54* (0.94)	– 1.03 (0.78)	1.57 (1.09)	– 1.01 (0.74)	– 1.24 (0.99)	– 0.44 (0.84)
Latin/Hispanic (Pop %)	1.13* (0.18)	1.39* (0.18)	0.20 (0.24)	0.64* (0.32)	0.47 (0.42)	– 0.34 (0.37)	– 0.14 (0.39)	0.35 (0.38)	0.66 (0.44)	0.63 (0.49)	1.12* (0.22)
Treated Units	75	75	75	75	75	75	75	75	75	75	75
Total Units	1,590	1,582	1,580	1,579	1,592	1,616	1,611	1,612	1,614	1,593	1,589
Adjusted R-Squared	0.18	0.22	0.18	0.18	0.17	0.18	0.23	0.18	0.17	0.15	0.15

** $p < 0.05$.*

CFHP = crime-free housing policy. Pop = population.

Source: Authors

Exhibit D.9

Regression Results by Map Rotation for Fremont, Unadjusted Spatial First Differences Model Using Continuous Treatment

	Angle=0	Angle=30	Angle=60	Angle=90	Angle=120	Angle=150	Angle=180	Angle=210	Angle=240	Angle=270	Angle=300
Number of CFHP Units	0.61* (0.03)	0.62* (0.03)	0.53* (0.03)	0.18* (0.02)	0.38* (0.03)	0.48* (0.04)	0.19* (0.02)	0.31* (0.04)	0.30* (0.03)	0.35* (0.03)	0.59* (0.03)
Rental Units (in hundreds)	0.18* (0.01)	0.17* (0.01)	0.11* (0.01)	0.19* (0.01)	0.21* (0.01)	0.13* (0.01)	0.19* (0.01)	0.26* (0.01)	0.17* (0.01)	0.17* (0.01)	0.16* (0.01)
Treated Units	32	32	32	32	32	32	32	32	32	32	32
Total Units	103	102	106	103	106	105	106	105	105	104	102
Adjusted R-Squared	0.28	0.28	0.16	0.16	0.18	0.14	0.15	0.21	0.13	0.16	0.26

$* p < 0.05$.

CFHP = crime-free housing policy.

Exhibit D.10

Regression Results by Map Rotation for Hayward, Unadjusted Spatial First Differences Model Using Continuous Treatment

	Angle=0	Angle=30	Angle=60	Angle=90	Angle=120	Angle=150	Angle=180	Angle=210	Angle=240	Angle=270	Angle=300
Number of CFHP Units	1.20* (0.04)	1.21* (0.04)	0.83* (0.04)	1.16* (0.05)	0.96* (0.05)	0.96* (0.05)	0.95* (0.06)	0.78* (0.05)	0.77* (0.03)	1.08* (0.04)	1.21* (0.05)
Rental Units (in hundreds)	0.40* (0.02)	0.39* (0.02)	0.51* (0.01)	0.45* (0.02)	0.46* (0.02)	0.47* (0.02)	0.48* (0.02)	0.60* (0.02)	0.50* (0.01)	0.47* (0.01)	0.48* (0.01)
Treated Units	12	12	12	12	12	12	12	12	12	12	12
Total Units	88	88	89	87	92	92	92	90	92	92	87
Adjusted R-Squared	0.38	0.37	0.35	0.36	0.28	0.28	0.28	0.34	0.29	0.33	0.41

$* p < 0.05$.

CFHP = crime-free housing policy.

Source: Authors

Exhibit D.11

Regression Results by Map Rotation for Riverside, Unadjusted Spatial First Differences Model Using Continuous Treatment

	Angle=0	Angle=30	Angle=60	Angle=90	Angle=120	Angle=150	Angle=180	Angle=210	Angle=240	Angle=270	Angle=300
Number of CFHP Units	0.21* (0.03)	0.47* (0.03)	0.42* (0.03)	0.52* (0.04)	0.41* (0.03)	0.38* (0.03)	0.26* (0.03)	0.17* (0.04)	0.26* (0.05)	0.17* (0.06)	0.20* (0.04)
Rental Units (in hundreds)	0.79* (0.02)	0.66* (0.02)	0.68* (0.03)	0.64* (0.03)	0.64* (0.02)	0.61* (0.03)	0.61* (0.02)	0.63* (0.03)	0.66* (0.03)	0.75* (0.03)	0.72* (0.03)
Treated Units	74	74	74	74	74	74	74	74	74	74	74
Total Units	178	177	175	179	185	185	183	182	181	181	182
Adjusted R-Squared	0.38	0.4	0.41	0.4	0.37	0.32	0.27	0.27	0.28	0.32	0.34

** $p < 0.05$.*

CFHP = crime-free housing policy.

Exhibit D.12

Regression Results by Map Rotation for San Diego County, Unadjusted Spatial First Differences Model Using Continuous Treatment

	Angle=0	Angle=30	Angle=60	Angle=90	Angle=120	Angle=150	Angle=180	Angle=210	Angle=240	Angle=270	Angle=300
Number of CFHP Units	0.14* (0.05)	0.24* (0.06)	0.44* (0.08)	0.40* (0.07)	0.77* (0.18)	0.24* (0.06)	0.13 (0.07)	0.21* (0.06)	0.31* (0.06)	0.37* (0.06)	0.51* (0.06)
Rental Units (in hundreds)	0.43* (0.07)	0.50* (0.09)	0.40* (0.10)	0.40* (0.10)	0.40* (0.09)	0.41* (0.11)	0.50* (0.09)	0.40* (0.11)	0.37* (0.10)	0.36* (0.10)	0.32* (0.09)
Treated Units	75	75	75	75	75	75	75	75	75	75	75
Total Units	1,590	1,582	1,580	1,579	1,592	1,616	1,611	1,612	1,614	1,593	1,589
Adjusted R-Squared	0.18	0.21	0.17	0.17	0.18	0.17	0.22	0.18	0.17	0.14	0.14

** $p < 0.05$.*

CFHP = crime-free housing policy.

Source: Authors

Exhibit D.13

Regression Results by Map Rotation for Fremont, Adjusted Spatial First Differences Model Using Continuous Treatment

	Angle=0	Angle=30	Angle=60	Angle=90	Angle=120	Angle=150	Angle=180	Angle=210	Angle=240	Angle=270	Angle=300
Number of CFHP Units	0.56* (0.03)	0.59* (0.03)	0.51* (0.03)	0.16* (0.02)	0.37* (0.03)	0.37* (0.03)	0.14* (0.02)	0.23* (0.04)	0.24* (0.03)	0.25* (0.04)	0.56* (0.03)
Rental Units (in hundreds)	0.18* (0.01)	0.17* (0.01)	0.12* (0.01)	0.21* (0.01)	0.20* (0.01)	0.11* (0.01)	0.22* (0.01)	0.25* (0.01)	0.17* (0.01)	0.16* (0.01)	0.16* (0.01)
Per Capita Income (in $10,000)	– 0.05* (0.02)	– 0.03 (0.02)	0.01 (0.02)	0.00 (0.02)	– 0.08* (0.02)	– 0.19* (0.03)	– 0.03 (0.02)	– 0.07* (0.02)	– 0.08* (0.02)	– 0.08* (0.02)	– 0.03 (0.02)
Asian (Pop %)	0.36 (0.27)	0.35 (0.26)	– 1.74* (0.35)	– 0.11 (0.16)	– 0.88* (0.44)	0.98* (0.35)	– 0.73* (0.32)	– 1.43* (0.44)	0.23 (0.35)	– 0.31 (0.30)	0.52 (0.27)
White (Pop %)	5.14* (0.67)	4.95* (0.64)	0.72 (0.70)	3.62* (0.44)	1.12* (0.53)	4.20* (0.58)	0.19 (0.38)	1.75* (0.84)	3.95* (0.66)	5.62* (0.57)	4.78* (0.56)
Black (Pop %)	1.37* (0.23)	1.40* (0.23)	– 0.69* (0.33)	2.12* (0.18)	– 0.32 (0.34)	1.07* (0.25)	0.08 (0.22)	– 1.31* (0.33)	0.52* (0.24)	– 0.61* (0.22)	1.55* (0.23)
American Indian/ Alaska Native (Pop %)	27.96* (2.62)	29.70* (2.52)	17.60* (1.95)	27.43* (2.32)	25.20* (2.03)	33.97* (2.68)	28.91* (2.41)	34.33* (3.62)	32.55* (3.07)	33.57* (2.70)	27.10* (2.50)
Latin/Hispanic (Pop %)	– 0.85* (0.33)	– 0.93* (0.33)	– 2.05* (0.45)	– 2.53* (0.19)	– 3.66* (0.41)	0.32 (0.40)	– 1.35* (0.33)	– 4.19* (0.60)	– 0.56 (0.43)	– 1.28* (0.40)	– 1.68* (0.37)
Treated Units	32	32	32	32	32	32	32	32	32	32	32
Total Units	103	102	106	103	106	105	106	105	105	104	102
Adjusted R-Squared	0.28	0.28	0.13	0.2	0.19	0.15	0.14	0.24	0.13	0.17	0.27

** $p < 0.05$.*

CFHP = crime-free housing policy. Pop = population.

Source: Authors

Exhibit D.14

Regression Results by Map Rotation for Hayward, Adjusted Spatial First Differences Model Using Continuous Treatment

	Angle=0	Angle=30	Angle=60	Angle=90	Angle=120	Angle=150	Angle=180	Angle=210	Angle=240	Angle=270	Angle=300
Number of CFHP Units	1.06* (0.06)	1.07* (0.06)	0.90* (0.06)	1.13* (0.06)	1.03* (0.07)	1.03* (0.07)	0.98* (0.07)	0.65* (0.06)	0.87* (0.03)	1.08* (0.04)	1.14* (0.06)
Rental Units (in hundreds)	0.50* (0.02)	0.50* (0.02)	0.57* (0.02)	0.47* (0.02)	0.49* (0.03)	0.50* (0.03)	0.53* (0.03)	0.71* (0.02)	0.56* (0.02)	0.53* (0.02)	0.57* (0.02)
Per Capita Income (in $10,000)	0.06* (0.03)	0.13* (0.03)	0.08* (0.04)	0.06 (0.03)	0.33* (0.07)	0.33* (0.07)	0.40* (0.08)	0.76* (0.07)	0.36* (0.06)	0.29* (0.06)	0.01 (0.04)
Asian (Pop %)	– 3.73* (0.42)	– 3.31* (0.46)	– 3.05* (0.43)	– 2.68* (0.56)	– 4.14* (0.62)	– 4.24* (0.63)	– 3.52* (0.64)	– 3.92* (0.60)	– 2.89* (0.60)	– 3.93* (0.48)	– 1.12* (0.56)
White (Pop %)	– 5.90* (0.64)	– 5.20* (0.56)	– 8.80* (0.63)	– 4.81* (0.46)	– 7.76* (0.38)	– 7.91* (0.39)	– 6.19* (0.38)	– 6.85* (0.43)	– 9.78* (0.46)	– 9.83* (0.55)	– 5.93* (0.56)
Black (Pop %)	– 4.84* (0.44)	– 4.50* (0.41)	– 4.88* (0.47)	– 3.99* (0.45)	– 5.32* (0.48)	– 5.34* (0.48)	– 4.13* (0.45)	– 4.39* (0.45)	– 6.01* (0.36)	– 6.55* (0.45)	– 4.19* (0.46)
American Indian/ Alaska Native (Pop %)	12.92* (1.57)	13.00* (1.56)	4.92* (1.04)	– 5.35* (1.03)	– 12.81* (2.00)	– 13.11* (1.97)	– 8.48* (2.04)	– 11.59* (2.92)	4.31* (1.94)	4.41* (1.93)	7.36* (1.44)
Latin/Hispanic (Pop %)	– 4.30* (0.39)	– 3.85* (0.35)	– 4.87* (0.42)	– 3.33* (0.43)	– 3.67* (0.42)	– 3.74* (0.42)	– 3.54* (0.44)	– 3.80* (0.33)	– 2.03* (0.30)	– 3.03* (0.29)	– 3.10* (0.43)
Treated Units	12	12	12	12	12	12	12	12	12	12	12
Total Units	88	88	89	87	92	92	92	90	92	92	87
Adjusted R-Squared	0.4	0.4	0.39	0.35	0.3	0.3	0.29	0.39	0.34	0.37	0.42

* $p < 0.05$.

CFHP = crime-free housing policy. Pop = population.

Source: Authors

Exhibit D.15

Regression Results by Map Rotation for Riverside, Adjusted Spatial First Differences Model Using Continuous Treatment

	Angle=0	Angle=30	Angle=60	Angle=90	Angle=120	Angle=150	Angle=180	Angle=210	Angle=240	Angle=270	Angle=300
Number of CFHP Units	0.31* (0.03)	0.46* (0.03)	0.43* (0.04)	0.59* (0.04)	0.47* (0.04)	0.47* (0.04)	0.37* (0.04)	0.26* (0.05)	0.39* (0.05)	0.28* (0.06)	0.31* (0.05)
Rental Units (in hundreds)	0.78* (0.02)	0.70* (0.03)	0.72* (0.03)	0.64* (0.02)	0.66* (0.03)	0.59* (0.03)	0.53* (0.03)	0.59* (0.04)	0.64* (0.04)	0.69* (0.04)	0.67* (0.03)
Per Capita Income (in $10,000)	0.21* (0.02)	0.26* (0.02)	0.27* (0.02)	0.24* (0.02)	0.40* (0.02)	0.24* (0.03)	0.17* (0.02)	0.16* (0.02)	0.22* (0.04)	0.25* (0.03)	0.15* (0.02)
Asian (Pop %)	0.45 (0.58)	– 4.75* (0.92)	– 4.31* (0.97)	– 3.03* (1.07)	2.04 (1.21)	2.34 (1.23)	5.30* (1.15)	7.20* (1.13)	6.51* (1.23)	6.52* (0.76)	2.25* (0.51)
White (Pop %)	– 5.62* (0.36)	– 7.10* (0.55)	– 6.49* (0.63)	– 6.21* (0.54)	– 4.86* (0.63)	– 2.37* (0.92)	2.86* (0.74)	– 0.05 (0.98)	– 1.59 (1.08)	– 0.44 (0.85)	– 1.93* (0.60)
Black (Pop %)	– 3.79* (0.19)	– 4.10* (0.34)	– 3.87* (0.34)	– 4.55* (0.28)	– 2.40* (0.24)	– 3.44* (0.32)	– 2.19* (0.24)	– 1.75* (0.23)	– 2.72* (0.32)	– 2.40* (0.20)	– 2.69* (0.17)
American Indian/ Alaska Native (Pop %)	6.67* (2.12)	5.88* (2.24)	4.84* (2.30)	2.02 (2.29)	1.09 (1.91)	– 0.79 (1.80)	12.53* (1.85)	9.54* (1.86)	7.92* (2.29)	3.33 (2.34)	4.91 (2.73)
Latin/Hispanic (Pop %)	1.70* (0.31)	– 0.23 (0.19)	0.14 (0.21)	1.00* (0.25)	1.41* (0.22)	0.88* (0.27)	2.60* (0.23)	2.01* (0.30)	1.31* (0.41)	2.48* (0.33)	2.62* (0.27)
Treated Units	74	74	74	74	74	74	74	74	74	74	74
Total Units	178	177	175	179	185	185	183	182	181	181	182
Adjusted R-Squared	0.43	0.42	0.42	0.43	0.39	0.34	0.32	0.3	0.31	0.35	0.38

* $p < 0.05$.

CFHP = crime-free housing policy. Pop = population.

Source: Authors

Exhibit D.16

Regression Results by Map Rotation for San Diego County, Adjusted Spatial First Differences Model Using Continuous Treatment

	Angle=0	Angle=30	Angle=60	Angle=90	Angle=120	Angle=150	Angle=180	Angle=210	Angle=240	Angle=270	Angle=300
Number of CFHP Units	0.10 (0.05)	0.20* (0.07)	0.45* (0.07)	0.40* (0.06)	0.76* (0.16)	0.26* (0.06)	0.16* (0.07)	0.21* (0.05)	0.28* (0.05)	0.33* (0.05)	0.44* (0.06)
Rental Units (in hundreds)	0.41* (0.07)	0.48* (0.09)	0.39* (0.10)	0.39* (0.10)	0.39* (0.09)	0.40* (0.11)	0.50* (0.09)	0.39* (0.11)	0.37* (0.11)	0.34* (0.11)	0.30* (0.09)
Per Capita Income (in $10,000)	0.01 (0.03)	0.02 (0.03)	0.03 (0.05)	0.07 (0.05)	0.01 (0.03)	0.05 (0.04)	0.18* (0.04)	0.07 (0.04)	0.03 (0.03)	– 0.04 (0.03)	– 0.12* (0.03)
Asian (Pop %)	1.63* (0.37)	1.03* (0.29)	1.22* (0.60)	1.71* (0.66)	0.53 (0.55)	1.01 (0.93)	0.33 (0.69)	0.99 (0.85)	– 0.18 (0.81)	0.22 (0.86)	1.68* (0.40)
White (Pop %)	3.23* (0.54)	2.86* (0.40)	4.51* (0.84)	5.24* (1.14)	1.51 (1.26)	2.55* (1.19)	2.74* (1.03)	3.86* (1.21)	1.46 (1.09)	2.09* (1.05)	2.19* (0.67)
Black (Pop %)	– 0.20 (0.35)	– 0.48* (0.22)	– 0.43 (0.44)	– 0.12 (0.46)	– 1.18* (0.48)	– 1.63* (0.57)	– 0.83 (0.58)	0.08 (0.70)	– 1.17 (0.61)	– 0.93 (0.63)	0.26 (0.25)
American Indian/ Alaska Native (Pop %)	0.73 (1.01)	– 1.11 (0.77)	– 2.60* (0.81)	– 2.36* (0.66)	– 4.25* (0.78)	– 4.57* (0.92)	– 0.89 (0.77)	1.63 (1.13)	– 0.97 (0.74)	– 1.32 (1.01)	– 0.59 (0.86)
Latin/Hispanic (Pop %)	1.14* (0.18)	1.40* (0.19)	0.24 (0.25)	0.62 (0.32)	0.42 (0.41)	– 0.34 (0.38)	– 0.10 (0.41)	0.40 (0.41)	0.71 (0.48)	0.61 (0.50)	1.12* (0.23)
Treated Units	75	75	75	75	75	75	75	75	75	75	75
Total Units	1,590	1,582	1,580	1,579	1,592	1,616	1,611	1,612	1,614	1,593	1,589
Adjusted R-Squared	0.18	0.22	0.18	0.18	0.18	0.18	0.23	0.18	0.17	0.15	0.15

** $p < 0.05$.*

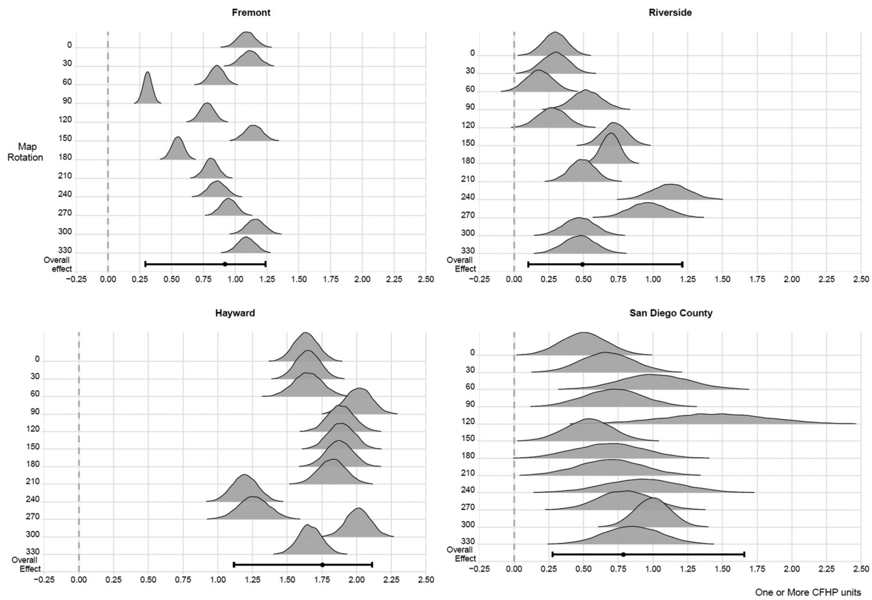
CFHP = crime-free housing policy. Pop = population.

Source: Authors

Appendix E. Estimated Average Treatment on the Treated Effects by Map Rotation, Model, and Location

Exhibit E.1

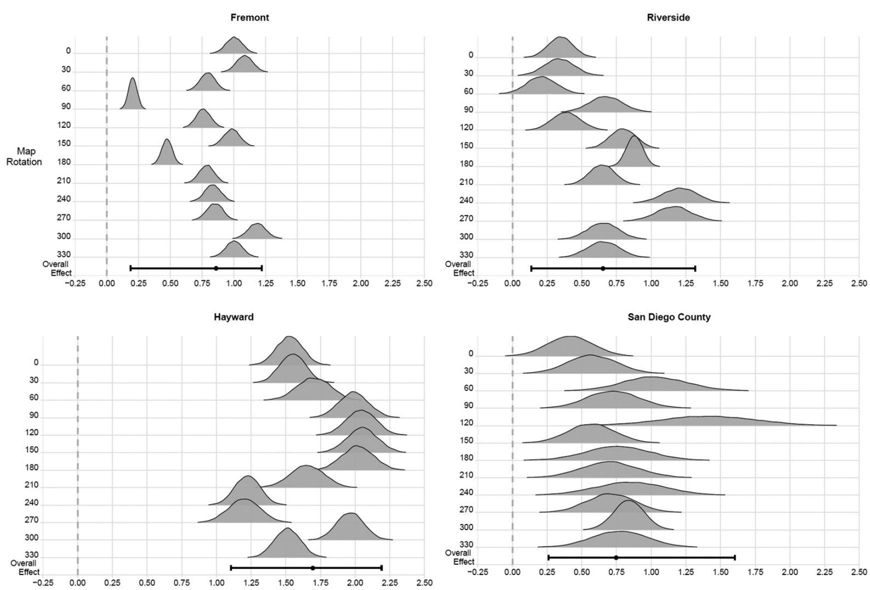
Unadjusted Models with Binary Treatment



Source: Authors

Exhibit E.2

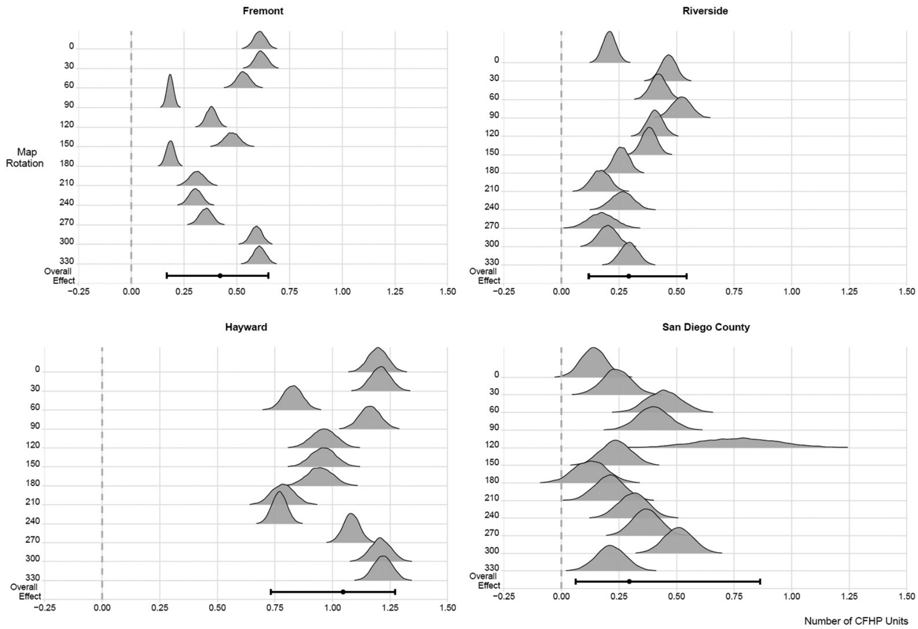
Adjusted Models with Binary Treatment



Source: Authors

Exhibit E.3

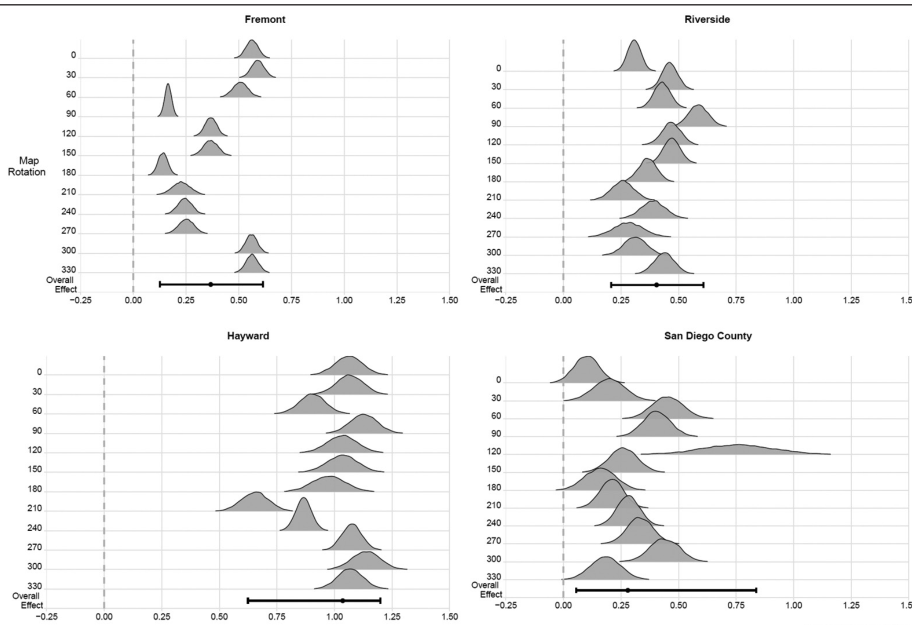
Unadjusted Models with Continuous Treatment



Source: Authors

Exhibit E.4

Adjusted Models with Continuous Treatment

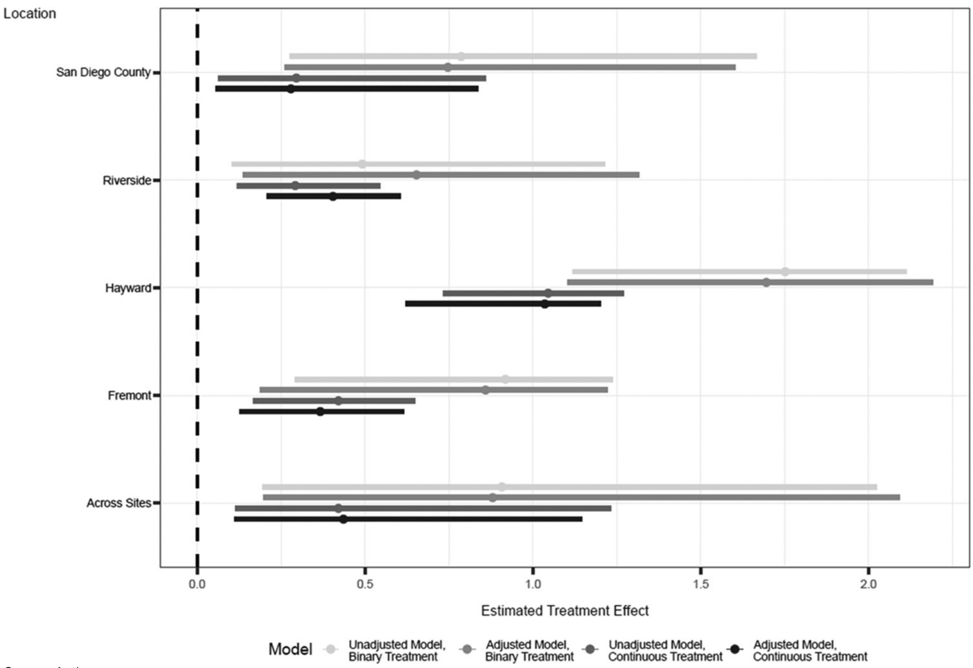


Source: Authors

Appendix F. Estimated Average Treatment on the Treated Effects by Model and Location

Exhibit F.1

Plot of Estimated Average Treatment on the Treated Effects by Model and Location



Source: Authors

Exhibit F.2

Table of Estimated Average Treatment on the Treated Effects by Model and Location (1 of 2)

Location	Specification	Treatment Measure	Estimated ATT
San Diego County	Unadjusted	Binary	0.786 (0.127, 1.683)
San Diego County	Adjusted	Binary	0.74 (0.077, 1.625)
San Diego County	Unadjusted	Continuous	0.3 (0.029, 0.887)
San Diego County	Adjusted	Continuous	0.279 (0.015, 0.858)
Riverside	Unadjusted	Binary	0.493 (0.104, 1.211)
Riverside	Adjusted	Binary	0.623 (0.128, 1.325)
Riverside	Unadjusted	Continuous	0.292 (0.119, 0.545)
Riverside	Adjusted	Continuous	0.419 (0.203, 0.592)
Hayward	Unadjusted	Binary	1.753 (1.117, 2.112)
Hayward	Adjusted	Binary	1.622 (1.078, 2.117)
Hayward	Unadjusted	Continuous	1.046 (0.733, 1.272)
Hayward	Adjusted	Continuous	0.986 (0.577, 1.171)
Fremont	Unadjusted	Binary	0.918 (0.293, 1.239)
Fremont	Adjusted	Binary	0.816 (0.259, 1.189)

Exhibit F.2

Table of Estimated Average Treatment on the Treated Effects by Model and Location (2 of 2)

Location	Specification	Treatment Measure	Estimated ATT
Fremont	Unadjusted	Continuous	0.421 (0.167, 0.65)
Fremont	Adjusted	Continuous	0.297 (0.066, 0.587)
Across Sites	Unadjusted	Binary	0.907 (0.17, 2.024)
Across Sites	Adjusted	Binary	0.869 (0.189, 2.024)
Across Sites	Unadjusted	Continuous	0.421 (0.095, 1.233)
Across Sites	Adjusted	Continuous	0.436 (0.07, 1.121)

ATT = average treatment on the treated.
Source: Authors

Appendix G. Example of a Writ of Execution Record

Exhibit G.1

Synthetic Data Replicating a Writ of Execution Record

A COUNTY SHERIFF'S OFFICE
Eviction List
12/01/2021 TO 12/31/2021

File Number	Occupants	Address	Restoration Date	Time	Status
0000000001	John Doe	2 Mayflower Ave. Marion, CA 28752	01/01/2020	12:00AM	SERVED
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	CANCELLED
[redacted]	[redacted]	[redacted]	[redacted]	[redacted]	CANCELLED
0000000002	Joe Bloggs	755 Campfire Ave. Hyde Park, CA 02136	01/02/2020	12:00AM	SERVED
0000000003	Jane Smith	936 Brickell Ave. East Brunswick, CA 08816	01/03/2020	12:00AM	SERVED

Source: Authors

Appendix H. Ordinary Least Square Models

Exhibit H.1

Unadjusted Models Using Binary Treatment

	Fremont	Hayward	Riverside	San Diego County
Intercept	0.01 (0.17)	0.01 (0.32)	0.25 (0.24)	0.31* (0.09)
One or More CFHP Units	1.06* (0.32)	1.86* (0.69)	0.32 (0.38)	0.63 (0.34)
Rental Units (in hundreds)	0.20* (0.06)	0.52* (0.10)	0.91* (0.09)	0.51* (0.02)
Treated Units	32	12	74	75
Total Units	118	100	201	1,754
R-Squared	0.31	0.36	0.42	0.24

** $p < 0.05$.*

CFHP = crime-free housing policy.

Source: Authors

Exhibit H.2

Adjusted Models Using Binary Treatment

	Fremont	Hayward	Riverside	San Diego County
Intercept	– 2.94 (2.77)	0.36 (3.10)	0.74 (1.94)	0.93 (1.01)
One or More CFHP Units	0.95* (0.35)	1.93* (0.70)	0.30 (0.38)	0.61 (0.34)
Rental Units (in hundreds)	0.19* (0.06)	0.62* (0.11)	0.88* (0.10)	0.48* (0.02)
Per Capita Income (in $10,000)	– 0.04 (0.13)	0.17 (0.21)	0.21 (0.18)	0.02 (0.05)
Asian (Pop %)	3.27 (2.89)	0.29 (3.27)	1.09 (2.53)	– 1.98 (1.05)
White (Pop %)	6.07 (3.64)	– 3.78 (3.63)	– 0.94 (3.24)	3.38* (1.28)
Black (Pop %)	2.07 (2.34)	– 1.07 (2.40)	2.91* (1.47)	– 1.20 (0.96)
American Indian/Alaska Native (Pop %)	10.17 (8.97)	12.72 (9.95)	1.78 (5.60)	1.82 (2.14)
Latin/Hispanic (Pop %)	1.95 (2.82)	– 1.58 (2.48)	1.49 (1.41)	0.98* (0.40)
Treated Units	32	12	74	75
Total Units	118	100	201	1,754
R-Squared	0.33	0.41	0.45	0.26

** $p < 0.05$.*

CFHP = crime-free housing policy. Pop = population.

Source: Authors

Exhibit H.3

Unadjusted Models Using Continuous Treatment

	Fremont	Hayward	Riverside	San Diego County
Intercept	0.04 (0.17)	0.15 (0.33)	0.32 (0.24)	0.32* (0.09)
Number of CFHP Units	0.48* (0.16)	1.07* (0.42)	0.23 (0.14)	0.18 (0.16)
Rental Units (in hundreds)	0.21* (0.06)	0.49* (0.11)	0.86* (0.09)	0.51* (0.02)
Treated Units	32	12	74	75
Total Units	118	100	201	1,754
R-Squared	0.3	0.36	0.43	0.24

** $p < 0.05$.*

CFHP = crime-free housing policy.

Source: Authors

Exhibit H.4

Adjusted Models Using Continuous Treatment (1 of 2)

	Fremont	Hayward	Riverside	San Diego County
Intercept	– 2.99 (2.80)	0.25 (3.12)	0.77 (1.92)	0.93 (1.01)
Number of CFHP Units	0.42* (0.17)	1.09* (0.42)	0.30* (0.14)	0.16 (0.16)
Rental Units (in hundreds)	0.22* (0.06)	0.58* (0.12)	0.79* (0.10)	0.48* (0.02)
Per Capita Income (in $10,000)	– 0.01 (0.13)	0.15 (0.21)	0.23 (0.18)	0.02 (0.05)
Asian (Pop %)	3.15 (2.95)	0.43 (3.29)	1.57 (2.51)	– 1.99 (1.05)
White (Pop %)	5.46 (3.70)	– 3.21 (3.64)	– 0.31 (3.22)	3.34* (1.28)
Black (Pop %)	1.88 (2.38)	– 0.58 (2.41)	– 4.5844	– 1.16 (0.96)

Source: Authors

Exhibit H.4

Adjusted Models Using Continuous Treatment (2 of 2)

	Fremont	Hayward	Riverside	San Diego County
American Indian/Alaska Native (Pop %)	12.70 (8.91)	14.59 (10.02)	1.03 (5.56)	1.92 (2.15)
Latin/Hispanic (Pop %)	2.30 (2.83)	– 1.56 (2.49)	1.63 (1.40)	0.97* (0.40)
Treated Units	32	12	74	75
Total Units	118	100	201	1,754
R-Squared	0.32	0.4	0.46	0.26

* $p < 0.05$.
CFHP = crime-free housing policy. Pop = population.
Source: Authors

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