Justice Divided, Justice Denied?
The Effects of Court Rules on Eviction Outcomes in Los Angeles County*

Matthew Estes† Kyle Nelson‡

May 25, 2025

Abstract

More than 40,000 households in Los Angeles County face eviction each year. Pursuing policies that reduce the number of evictions is of growing importance to state and local policymakers, but the causes and consequences of eviction are poorly understood. By collecting eviction docket records and linking them to administrative data, we are able to study an important institutional determinant of eviction in LA County: how courts assign cases. Because eviction cases are assigned to courthouses based on a unique spatial assignment rule, we test the effect of court assignment on default eviction probability using a regression discontinuity design. We show that courthouse assignment can increase the probability of default eviction by 0.7–23.1 percentage points.

Keywords: eviction, court rules, regression discontinuity, empirical legal studies

*Estes acknowledges this work was supported by the Haynes Lindley Doctoral Dissertation Fellowship. The views expressed herein are those of the authors and do not necessarily reflect the views of the Haynes Foundation. We are also grateful to Mike Alvarez, Ransi Clark, Danny Ebanks, Rebecca Jean Emigh, Jim Greiner, Jonathan Katz, Mitchell Linegar, Jean-Laurent Rosenthal, and Bob Sherman for helpful comments and feedback on this project.

†California Institute of Technology. mestes@caltech.edu

‡University of California, Los Angeles. kyle.robert.nelson@gmail.com

1 Introduction

Landlords file more than 40,000 eviction cases against renter households each year in Los Angeles County. The leading reason is non-payment of rent. In most LA neighborhoods, more than 90% of eviction notices are issued for non-payment of rent. Once filed, most cases end in eviction via a default judgment, where the court orders the tenant(s) to vacate the property and, if relevant, pay the landlord any unpaid rent. For tenants, the repercussions are increased housing instability, reduced earnings, reduced credit access, and increased hospital visits.[1]

With the expiration of COVID-19 eviction protections, state and local policymakers are increasingly exploring interventions to decrease eviction filings and keep tenants housed. California Gov. Gavin Newsom, for example, signed housing reforms in 2023 oriented toward decreasing the number of evictions.[2] Local jurisdictions across the state have gradually begun to adopt more stringent tenant protections too. In the City of Los Angeles, Mayor Karen Bass has extended rent relief programs, stating: "We will do all we can to ensure that a wave of evictions does not hit our City as we continue confronting the homelessness crisis."[3]

Despite policymaker interest, the causes of eviction are not well-understood. Part of the problem is that data on California evictions is scarce and difficult to obtain, which has prevented researchers from fully identifying institutional mechanisms linking eviction filings with eviction case outcomes. This paper assembles the most comprehensive data on LA County evictions to-date. Our primary dataset for this paper consists of over 60,000 individual case docket records, which we use to better understand individual tenant outcomes and link to detailed property assessment data.

First, we use this data to isolate descriptive trends in LA County. We show that case times are increasing from 2016–2023. Then, we explore the court's zip code-based assignment and show that misfiling occurs: a small number of eviction cases (2-5%) are filed in an incorrect courthouse each year in our dataset. We do not, however, find evidence that misfiling is attributable to strategic landlord behavior.

Using this novel data, we next study court assignment as an institutional determinant of eviction via default judgment in LA County. Default evictions occur when tenants fail to appear at court and lose *by default.* We quantify how the court assignment mechanism impacts the eviction default probability. Because LA County

[1] See Collinson et al. (2024).
[2] For media coverage, see Wiley (2023).
[3] Mayor (2023).

eviction cases are assigned to courthouses based on a unique spatial assignment rule, we are able to estimate the causal effect of courthouse assignment on default probability using a regression discontinuity design. The discontinuity design allows us to compare cases located across a courthouse boundary that are likely to be similar along unobservable dimensions.

We show that—for renters near a courthouse boundary—court assignment meaningfully affects the eviction default probability. Our estimates for the local average treatment effect (LATE) of courthouse assignment range from 0.7–23.1 percentage points for seven different courthouse pairs. For example, for renters near the Santa Monica & Stanley Mosk courthouse boundary, the average treatment effect of being assigned to the Santa Monica courthouse is a 6.23 percentage point increase in the probability of default versus the Stanley Mosk courthouse.

To further explain the causes of eviction default, we explore how distance to court impacts default probability. As another author writes:

> "[T]he inability to access justice is rooted in something more physical, more mundane: the many and varied costs of getting to and physically using a brick-and-mortar courthouse."[4]

Specifically, we test whether courthouse assignment effects the expected default eviction probability for renters near the boundary with the same distance to assigned court. Our estimates for the conditional local average treatment effect (CLATE) at the seven courthouse boundaries show heterogeneous effects of distance to court on renters in LA County.

Our analysis informs ongoing policy debates. Typically, interest groups propose eviction reforms to give tenants more resources. For example, some tenant advocates[5] endorse civil *Gideon*,[6] a right-to-counsel intervention. But providing tenants with legal representation in eviction court is costly. By contrast, this paper is concerned with institutional policy reforms. We show how courthouse assignment is an important institution with a disparate impact on tenants across courthouse boundaries. Because LA County has 23 active courthouses—including six[7] that previously heard

[4] Prescott (2017).

[5] See, e.g., Baird (2021).

[6] The proposal is a reference to *Gideon v. Wainwright* (1963), the landmark Supreme Court decision requiring states to provide defense counsel to indigent criminal defendants.

[7] Previous Eviction Courthouses (with year last heard eviction cases): Alhambra (2013), Beverly Hills (2012), Burbank (2013), Glendale (2013), Pomona (2017), Torrance (2013).

eviction cases post-2010—policymakers can modify the courthouse assignment rule to minimize the cost of getting to court.[8]

1.1 Prior Literature

This paper is related to a growing eviction literature that has, to date, been primarily published in fields like sociology, urban planning, and policy studies. Research from the Eviction Lab (Desmond, 2017), for example, discusses the demographic correlates of eviction, suggesting that defaults are randomly distributed.[9] In LA County, by contrast, Lens et al. (2020) and Nelson et al. (2021) demonstrate the importance of neighborhoods, housing markets, and spatial clustering to understanding eviction dynamics (the "geography of risk") in metropolitan areas. Larson (2006) similarly shows that case characteristics and neighborhood-level covariates are important determinants of a prevalent eviction outcome: default. This literature informs our research design. Intuitively, the regression discontinuity design disentangles correlation from causation by comparing cases located nearby so that observable and unobservable characteristics are similar across the courthouse boundary.

We also contribute to a nascent but growing literature on the causal determinants of eviction outcomes. Our work is related to Hoffman and Strezhnev (2023), who study the spatial determinants of Philadelphia evictions. Studying over 200,000 eviction cases in Philadelphia from 2005–2021, the authors use a selection-on-observables strategy with a variety of fixed effects to show that "a one hour increase in estimated travel time increases the probability of default by between 3.9 to 8.6 percentage points across different model specifications." In New York City and Chicago, Collinson et al. (2024) study the consequences of eviction using detailed administrative data. Using a judge-leniency design ("Judge IV"), the authors show that eviction increases homelessness, reduces earnings, and negatively impacts credit access.

Our work adds to this causal determinants of eviction literature by incorporating a regression discontinuity design in a sprawling Western city. This is important for two reasons. First, the quasi-experimental regression discontinuity design is said to have high degrees of internal validity.[10] Second, it is important to study Western cities that differ in important ways from Philadelphia, NYC, and Chicago to test the generalizability of prior work. LA County is likely more representative of Sunbelt

[8] We leave the optimal eviction courthouse assignment policy for future work.

[9] See Desmond (2017) p. 358, n. 5.

[10] See, e.g., Lee and Lemieux (2010).

cities—in terms of spatial distribution of cases, transit infrastructure, commute time, etc.—than, e.g., Philadelphia. Moreover, the assignment process in LA County differs in significant respects from assignment in these three best-studied cities: for example, cases in Philadelphia are assigned to a single courthouse located at the intersection of the city's two primary public transit lines.[11] By contrast, LA County cases are assigned to 1 of 11 courthouses by a unique neighborhood-zip code scheme. Like Hoffman and Strezhnev (2023), we show that distance does matter in LA County, although there is important geographic heterogeneity.

Finally, we contribute to the law and economics literature on proximity or access to court. Prescott (2017), for example, studies how the introduction of dispute resolution platforms impacted case times and case default rates. Like Prescott (2017), we show physical space affects case default rates.

The rest of the paper is organized as follows. Section 2 presents the institutional details necessary to understand eviction in Los Angeles County.[12] Section 3 describes the collected data, defines the outcome-of-interest, and documents descriptive findings. Section 4 describes the regression discontinuity design and results, including: identification, estimation, local average treatment effects (LATE), and conditional local average treatment effects (CLATE). Section 5 concludes.

Further details can be found in the Appendices on data sources and collection, data cleaning, record linkage, descriptive findings, and other details.

2 Institutional Background

Although previous studies on eviction have focused on major metropolitan areas such as NYC and Chicago, fewer academic works concern evictions in California cities. Despite the consistently high volume[13] of eviction filings and policymaker concern, it is difficult to address CA eviction problems because empirical work is hampered by

[11]Cook County cases are heard at six different courthouses, although Chicago cases are heard downtown at the Daley Center. The suburban cases are assigned to one of the five suburban courthouse districts. The cities assigned to each district are listed at https://www.cookcountyclerkofcourt.org/divisions/suburban-districts-0. In New York City, eviction cases occur in seven courthouses determined either by County (Bronx, Kings, New York, Queens, Richmond) or two special eviction courthouses (Harlem and Red Hook).

[12]Certain institutional details cannot be treated fully here. We describe only the eviction details necessary to contextualize our identification strategy and interpret the results. For a more complete treatment of LA County eviction, including historical details, see Nelson (2023).

[13]See the Eviction Lab estimates in the top left panel of Figure F1. The Eviction Lab-modeled estimates also show that LA filings constitute a roughly constant proportion of total statewide filings from 2000–2018.

data availability problems. California counties do not uniformly record or report the number of cases filed by different types (e.g. eviction, small claims, and unlimited civil jurisdiction). The statewide eviction record sealing law is another obstacle. Under CA law, many eviction records are sealed to the public unless certain conditions are met.[14] Simplifying, eviction records are sealed unless the landlord prevails at trial or the case ends in a default judgment against the tenant.

Due to these reporting and sealing issues, we study a particular eviction outcome—eviction via default judgment. Defaults can occur at two time points in an eviction lawsuit: first, if tenants do not file an Answer before the court-mandated deadline, and second, if tenants do not appear at an assigned court date. While the latter type is relatively rare, both types of default result in landlords winning and tenants losing their cases, oftentimes before their first court date. Because defaults are difficult to reverse, filing an Answer and attending eviction court dates are imperative.

There exist myriad obstacles, however, to getting to court. As argued most relevantly by tenants-plaintiffs in *Miles v. Wesley*, 801 F.3d 1060 (9th Cir. 2015):

> [R]educing the number of courthouses handling unlawful detainer cases disproportionately impacts poor, disabled, and minority residents. ... [B]ecause individuals with disabilities and minorities are disproportionately renters who rely on public transportation, the closure of these courtrooms would have a disparate impact on these communities. [T]he importance of neighborhood court access is heightened in light of the expedited timeline of unlawful detainer actions, the fact that most low-income tenants are not represented by counsel, and the prospect that a default judgment could render a tenant homeless.

In response to *Miles*, the LA Superior Court system expanded the number of regional courthouses that process eviction cases, but many of the distance concerns cited in *Miles* continue to exist. Hoffman and Strezhnev (2023) confirmed anecdotal evidence in *Miles*, showing that longer travel times made tenants in Philadelphia, PA and Harris County, TX more likely to default than tenants with shorter travel times. The authors find that this “transit effect” disappeared when courts made virtual accommodations in eviction proceedings during the COVID-19 pandemic.

This growing literature focuses primarily on structural factors that shape the likelihood of tenants defaulting. To the extent that this research identifies institutional

[14]See California Code of Civil Procedure §§ 1161.2, 1167.1.

determinants of default, it focuses on COVID-19 era adaptations, rather than eviction case policies in less exceptional times. By contrast, our paper is the first to empirically assess how an idiosyncratic institutional process—court assignment of eviction cases to regional courtrooms within a broader countywide court system—affects the likelihood of tenant default.

To do so, we collected comprehensive data on monthly eviction filings in LA County.[15] The top right panel of Figure F1 shows the LA County filing volume data we collected via California Public Records Act (CPRA) requests to the LA Superior Courts (LASC). Our filing data augments the Eviction Lab Data (Figure F1 top left panel) with exact filing volumes since 2000 and emphasizes the inclusion of 2019–2023 filings. Although eviction filings were low in 2020–2022 due to temporary eviction protections at the local, state, and federal levels, the number of eviction filings in 2023 exceeded the number of pre-pandemic filings in the 2017–2019 years.

During the same period, the time to complete an eviction case has been increasing. In the bottom panel of Figure F1, the percentage of CA eviction cases disposed in 30 or 45 days decreased from 2014–2023. Eviction is a summary proceeding, but only 35% of the California evictions filed in 2023 were completed within 45 days. In Appendix C and Appendix D, we show that LA County also experiences longer disposition and total case times.

In sum, LA County evictions are increasing in volume, take longer to complete, and are difficult to address due to lack of reliable empirical information for policymakers, legal officials, and researchers. This paper is the first to look at the relationship between institutional processes and default outcomes and represents the most comprehensive empirical description and causal analysis of how the LA County eviction process impacts eviction outcomes to-date. The remainder of Section 2 describes the LA County eviction system: Section 2.1 describes the eviction process; and Section 2.2 explains how eviction cases are assigned to different eviction courthouses.

2.1 Eviction Process

The eviction process begins when a landlord serves an eviction notice on a tenant. The vast majority of eviction notices are for unpaid rent: for example, in LA City, over 96% of the notices in 2023 were for non-payment of rent. Eviction notices typically give tenants 3 days (91% of eviction notices in LA City) to "cure" their lease breach by paying unpaid rent to the landlord. The amount of unpaid rent and number of

[15] See Appendix F.

eviction notices vary at the zip-code and building levels.[16]

Next, the landlord initiates an eviction proceeding by filing an eviction lawsuit in the LA Superior Court system, which costs $240-$385.[17] After being notified of an eviction proceeding initiated against them,[18] tenants must file an Answer within 5 days (pre-2025)[19] with the court.[20] The filing fee for the tenant's Answer has varied over time, but the 2024 fee in eviction actions where the contested amount of rent is less than $12,500 is $225.[21]

If tenants do not file an Answer by the court-mandated deadline, landlords may petition the court to enter a default judgment against the tenant. Otherwise, after an Answer is filed, the court sets a trial date. Tenants who do not appear at trial will also receive a default judgment, but if they appear there is a judgment on the merits. The judgment typically awards landlords any past due rent.

Following the court-issued judgment, the landlord may enforce the judgment by obtaining a writ of execution. The writ gives the sheriff permission to lock the tenant out of the premises. After obtaining the writ, the sheriff will serve the tenant a Notice to Vacate, which gives the tenant five days to move out. Five days after receipt of the Notice to Vacate, the sheriff will change the locks, forcing the tenant out of the residence. The typical process is represented graphically below in Figure 1.

[16] See Nelson et al. (2021) for discussion of the spatial autocorrelation in eviction variables.

[17] See nos. 11 and 14 in LASC (2024).

[18] Tenants are considered notified after being served the Summons and Complaint forms.

[19] The five days do not include weekends or holidays. Additionally, tenants may have longer to respond if they are improperly served. But see Assembly Bill 2347, which as of Jan 2025 gives tenants 10 days to respond.

[20] The tenant is not supposed to mail the Answer, as they will default if the Answer doesn't arrive. The official self-help page for California Courts strongly recommends against mailing the Answer, and instead says you should show up to file the Answer at the relevant court. See `https://selfhelp.courts.ca.gov/eviction-tenant/respond-file`.

[21] See no. 15 in LASC (2024). But note that there are fee waiver applications available.

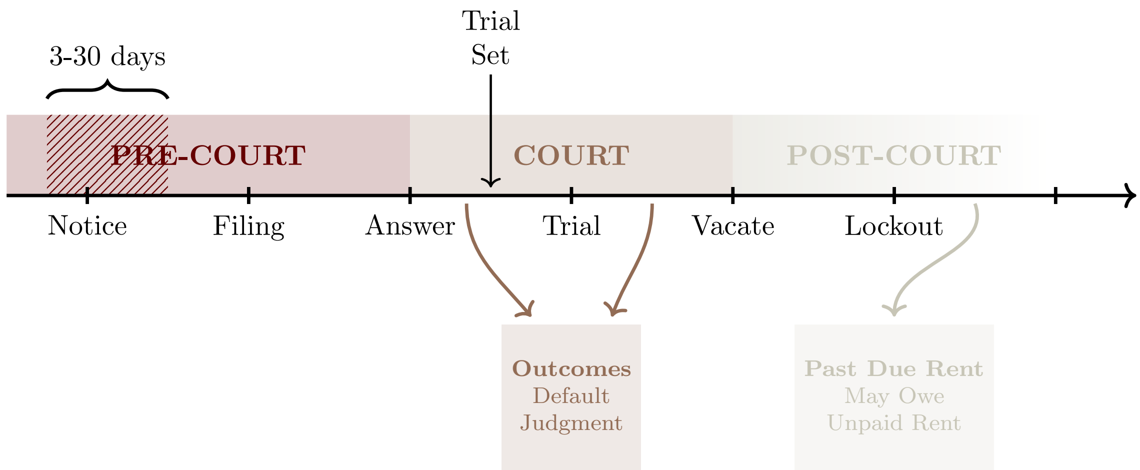


Figure 1. Eviction Timeline (Simplified)

This is a stylized timeline of events, which may not reflect the exact process for every eviction.[22] In particular, eviction moratoria and other COVID-19 protections altered the 2020–2022 process, e.g., giving tenants more time or limiting the landlord's ability to force the tenant to vacate. We document, moreover, in Appendix C and Appendix D that time-to-disposition and total case times have recently increased.[23]

2.2 Courthouse Assignment Mechanism: Map & History

According to LASC Local Rule 2.3(a)(2), eviction cases are assigned to courthouses based on a unique spatial mechanism. Under that rule, unlawful detainer actions:

> "must be filed in the courthouse serving the location and proper United States Postal Service zip code of the property in dispute using the Zip Code Table for Unlawful Detainer cases."

The eleven courthouses where eviction cases are filed include: Chatsworth, Compton, Governor George Deukmejian (Long Beach), Inglewood, Michael Antonovich Antelope Valley, Norwalk, Pasadena, Santa Monica, Stanley Mosk, Van Nuys East, and West Covina. Table 1 below illustrates how the courthouse assignment procedure works for the first few zip codes in Los Angeles County.

[22] The eviction timeline outlined above omits, for instance, any special motions that may arise.
[23] This accords with the statewide trend in the bottom panel of Figure F1.

Table 1. Zip Code Table for Unlawful Detainer Cases

Zip Code	City/Neighborhood	Modifier	Courthouse
90001	FLORENCE		Stanley Mosk
90001	HUNTINGTON PARK		Norwalk
90001	LOS ANGELES		Stanley Mosk
90002	FLORENCE		Compton
90002	LOS ANGELES		Compton
90002	LYNWOOD		Norwalk
90002	WATTS		Compton
90003	LOS ANGELES	North of Manchester	Stanley Mosk
90003	LOS ANGELES	South of Manchester	Compton
90004	LOS ANGELES		Stanley Mosk

Generally, the city-zip code pairs completely determine the assigned courthouse. However, in some zip codes the assignment is further determined relative to a particular street. For example, in Table 1 above, eviction cases arising in the 90003 zip code are assigned to the Stanley Mosk or Compton Courthouse if the tenant's address is north or south of Manchester Avenue, respectively. The full assignment map for LA County is given below in the left panel of Figure 2.

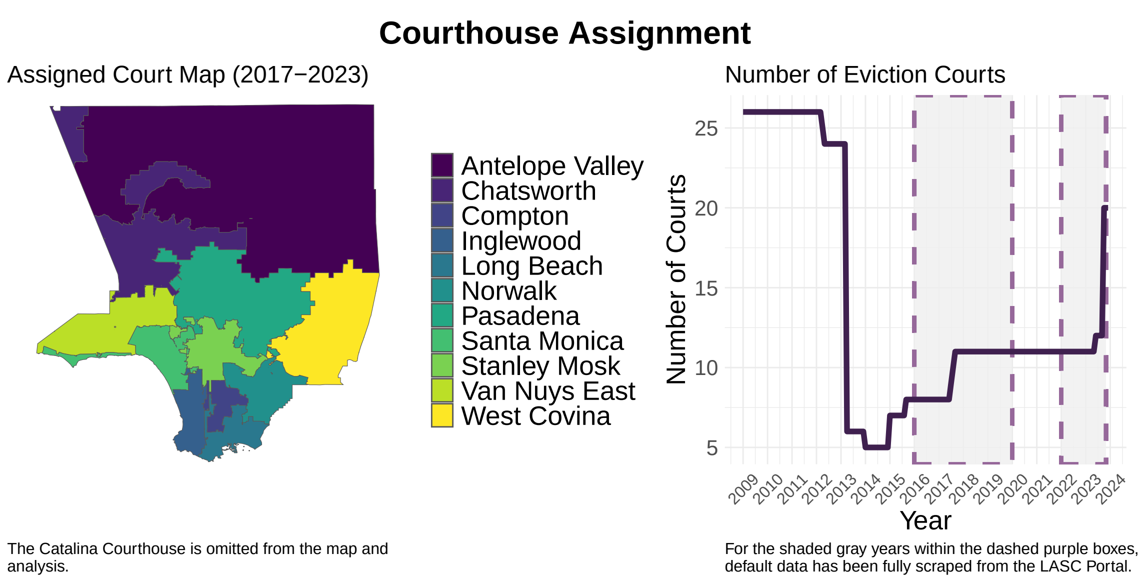


Figure 2. Courthouse Assignment
Note: The left panel shows the courthouse districts from 2017-2023, found by aggregating the units from the Simplified Zip Code Table (Table A2). The right panel is the number of eviction courts from 2009-2024.

Over time, the number of courthouses that hear eviction cases in LA County has fluctuated. As seen in the right panel of Figure 2 above, the number of courthouses that hear eviction cases has ranged between a low of five courthouses (2014) and a high of twenty-six courthouses (2009-2011). This paper focuses on the period with 11 courthouses (mid-2017 to 2023), which is the long horizontal line in the right panel of Figure 2.[24] See Appendix A for more details on assignment.

3 Data and Outcomes

This section describes the data collection (inc. geocoding), the outcome-of-interest (default eviction), and descriptive trends.

3.1 Docket Records: Geocoding & Assessor Linkage

The first and most important dataset we collected for this paper includes tens of thousands of individual docket records in eviction cases scraped from the LA Superior Courts from 2016-2023.[25] From the individual-level text files containing all publicly-available docket information, we use regular expression (regex) to extract detailed information for each individual case, including the following covariates: landlords (plaintiffs), tenants (defendants), attorneys (if applicable), address information, monetary awards, judge, courthouse, and dynamic case timing information. Particularly important is the address information, which includes the full address (i.e. street number, street, city, state, zip code) for the majority of cases across years.

Using the individual-level case address information, we then geocoded each address using the Mapbox API. The Mapbox API returns probabilistic matches with a matched address, latitude/longitude, and the match "confidence" score. In the analyses that follow, we consider only cases for which the Mapbox API returns a "High" or "Exact" match for the address we extracted from the individual docket records.

Using the geocoded addresses, we then linked our eviction dataset to information from the LA County Assessors Office. This gives us building-level covariates for each address and includes, for example, the age of the building, the number of units, and number of bathrooms. Many of these covariates serve as important proxies for tenant

[24] We focus on the primary 11 courthouses, although technically the Catalina Courthouse also hears eviction cases for Santa Catalina Island. Unless otherwise stated, we generally do not consider this court because it has no observed evictions. We therefore omit it from the Figure 2 plots.

[25] Unless otherwise noted, we exclude 2020-2022 from all analysis and discussion because of local, state, and national eviction moratoria.

income or tenant rent, which are generally unobservable. Note that, for each year, we use assessor data on the number of units in a building to infer the number of units in that building for which we do *not* observe default.

See Appendix B for more details on data collection, including information on the case availability, the FOIA data on the total number of evictions in a courthouse each month, sampling rates in Figure B1, and geocoding information in Figure B2.

3.2 Outcome: Eviction Default

The main outcome of interest in this paper is eviction default. Using the docket and assessment data, we measure the number of eviction defaults each year at each address. The primary outcome is a binary variable that reflects whether we observe a rental unit i experience an eviction default in year t:

$$\text{eviction}_{it} = \mathbf{1}\{\text{unit } i \text{ is evicted via default}\}$$

Note that, in the analysis that follows, we focus on the sub-population of buildings in a given year that have at least one observed eviction. We exclude all other buildings that appear in the LA County assessor data but do not match an address in our scraped eviction data. Assessed properties for which we do not observe an eviction may differ from properties with evictions in important but unobservable respects. Note that the binary nature of this outcome will allow us to interpret the conditional expectation $\mathbb{E}[\text{eviction}_{it}|X_i = x]$ as the probability of default eviction for units i that are x distance from the courthouse district boundary conditional on being an address with at least one rental unit with eviction default.

3.3 Docket Records: Descriptive Findings

The docket records are important for empirically assessing eviction trends. Here, we document two particular descriptive findings: (1) case times are increasing in LA County from 2016 to 2023; and (2) a number of eviction cases are filed in the wrong court but this is not attributable to strategic landlord behavior.

3.3.1 Default Times

Using the docket data, we first show that the statewide trend toward longer case times also holds in LA County. To do so, we compute two timing measures. The first measure is the time-to-default: the number of days from the assignment of the case to a judge and the first entry of the default judgment on the docket. For each default case j, this is computed as follows:

$$\text{time-to-default}_j = \text{default entered on docket}_j - \text{judge assigned}_j$$

In some cases, the docket record is missing the date default judgment is entered.[26]

The second measure calculates the total case time in case j. Using regular expressions, we extract all dates of the format "MM/DD/YYYY". We then compute the difference between the earliest and latest date in case j:

$$\text{total time}_j = \text{latest date on docket}_j - \text{earliest date on docket}_j$$

This measure is computed for every case in our dataset.

Using these measures, we observe that the time-to-default and total case times are highest in 2023. For example, Figure C1 shows the 2023 time-to-default density is shifted significantly further rightward than pre-pandemic years. This is consistent with the statewide trend (bottom panel of Figure F1). See Appendix C and Appendix D for additional details and alternative time measures.

3.3.2 Misfiled Eviction Cases

Next, we discuss misfiled eviction cases. Misfiling is when a docket record's observed courthouse does not match the proper filing courthouse from the LA County Zip Code assignment rule (Table 1). Because the misfiling classification is map-dependent, we proceed conservatively. Specifically, we assume that, in each neighborhood-zip pair, the majority of cases are filed in the correct courthouse. Even under this assumption, approximately 2.3% of the eviction cases are misfiled (2018, 2019, 2023). Using our preferred map (see Appendix A), 5.5% of cases are misfiled (2018, 2019, 2023).

Here, we explore one possible explanation for misfiling: landlords—knowingly or unknowingly—file in the incorrect courthouse. Misfiling is not necessarily nefarious, as it could be due to confusion or lack of information. Indeed, in some regions with misfiled cases the assignment rule (Table 1) is relatively complicated.[27] Alternatively, landlords may strategically disadvantage tenants by misfiling in distant courthouses.

Using the docket records, we test whether landlords strategically disadvantage tenants by filing in more distant courthouses. To test whether landlords are strategic,

[26] See Appendix C for full details.

[27] Meaning the assignment rule does not pick out one unique courthouse for the zip code.

we compare two distance histograms. In Figure 3, the red histogram is the distance from the tenant address to the assigned courthouse, whereas the blue histogram is the distance from the tenant address to the observed filing courthouse.

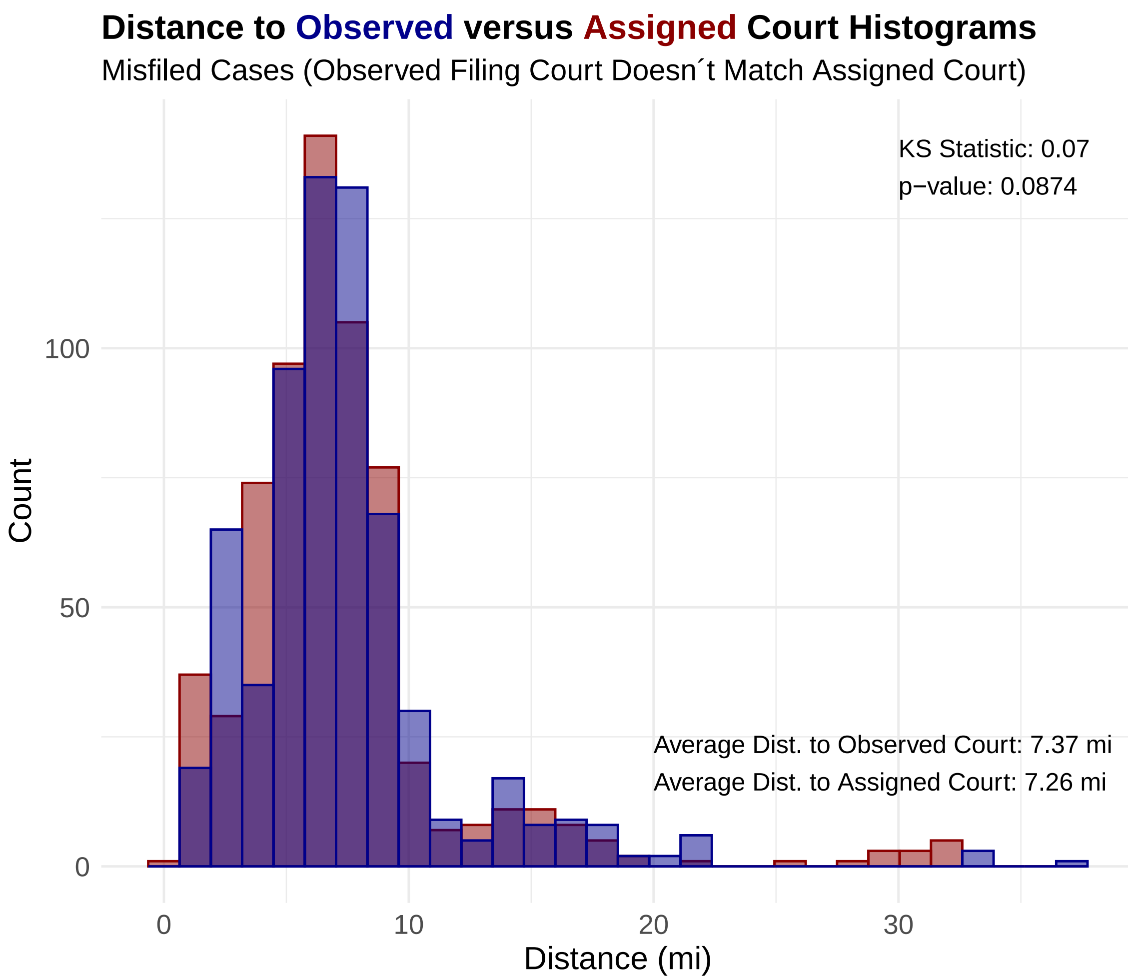


Figure 3. Misfiled Cases: Distance to Observed vs Assigned Court
Note: The blue histogram is the distance to observed court (among misfiled cases) and the red histogram is the distance to the assigned court (among misfiled cases). The KS statistic can be used to test the null hypothesis that the distances are drawn from the same distribution.

Although the average distance to the observed courthouse is 0.11 miles further for tenants, we cannot statistically distinguish between the two distributions ($p \approx 0.0874$) using the standard KS test. In other words, there is no statistical evidence of landlord strategic filing to disadvantage tenants among the cases we here label misfiled.

It has long been recognized that clear legal rules lower legal costs and reduce uncertainty.[28] An unclear procedural rule like the LA County eviction assignment mechanism can be clarified or refashioned. Although the optimal assignment rule is beyond the scope of this paper, we have identified some neighborhood-zip pairs (e.g. Hyde Park in Figure H1) where there is—at least in practice—procedural uncertainty.

In what follows, we focus on correctly filed cases only. See Appendix A for further details on the assignment map, and Appendix H for further discussion of misfiling.

4 Regression Discontinuity Design: Methods & Results

This section explains our regression discontinuity design (RDD), which exploits variation stemming from the discontinuous assignment of cases to courthouses based on spatial location. We present results estimating the local average treatment effect (LATE) and the conditional local average treatment effect (CLATE) for seven different courthouse pairs across LA County.

4.1 Continuity-Based RDD

In what follows, we consider the "sharp" regression discontinuity design.

4.1.1 Setup & Identification

To begin, we assume a potential outcomes framework. Let Y_{0i} and Y_{1i} be the counterfactual outcomes for an individual i without and with treatment, respectively. Let the "forcing variable" be X_i be the distance to the boundary C. The binary treatment W_i is determined as follows:

$$W_i = \mathbf{1}\{X_i \geq C\}$$

The observed outcome is:

$$Y_i = (1 - W_i)Y_{0i} + W_i Y_{1i}$$

Define further the counterfactual conditional expectation functions (CEF):

$$\mu_g(x) = \mathbb{E}[Y_g | X = x]$$

for $g = 0, 1$. In the regression discontinuity design, the potential outcome CEFs are assumed continuous in the forcing variable X. Because W_i is a deterministic function

[28] See, e.g., Kaplow (1992).

of X_i note that ignorability (conditional mean independence) holds:

$$\mathbb{E}[Y_g|X, W] = \mathbb{E}[Y_g|X]$$

for $g = 0, 1$.

The estimand of interest in a sharp RDD is the treatment effect at the cutoff, or the local average treatment effect (LATE), defined as:

$$\tau_C = \mathbb{E}[Y_1 - Y_0|X = C]$$

In our empirical setting, we have a treatment effect for each pair of courthouse districts that share a boundary C. That is, for each pair of courthouse districts, we define treatment $W_i = 1$ if unit i is in the first courthouse district and $W_i = 0$ if unit i lies in the other courthouse district. For example, when comparing buildings near the Pasadena and West Covina courthouse boundary, we set $W_i = 1$ if unit i is assigned to the Pasadena courthouse and $W_i = 0$ if assigned to the West Covina courthouse.

Because prior research suggests distance to court is an important determinant of the default probability ((Hoffman and Strezhnev, 2023)), we also consider the conditional local average treatment effect (CLATE), defined as:

$$\tau_C(z) = \mathbb{E}[Y_1 - Y_0|X = C, Z = z]$$

where Z_i is the distance for case i to assigned courthouse. We assume that $\mathbb{E}[Y_g|X = x, Z = z]$ is continuous in x for each $g = 0, 1$ and for all $z \in \text{supp}(Z)$. Below, we explore the heterogeneous effects $\tau_C(z)$ as a function of the conditioning variable Z.

Under these assumptions, the LATE is identified by the limits of the observable CEFs:

$$\tau_C = \lim_{x \to C^+} \mathbb{E}[Y|X = x] - \lim_{x \to C^-} \mathbb{E}[Y|X = x]$$

and similarly, for each z-value, the CLATE is identified by:

$$\tau_C(z) = \lim_{x \to C^+} \mathbb{E}[Y|X = x, Z = z] - \lim_{x \to C^-} \mathbb{E}[Y|X = x, Z = z]$$

4.1.2 Estimation & Inference

Estimating the limits that identify the causal estimands above is usually accomplished non-parametrically. Below, we use the local linear estimator with uniform kernel as in Imbens and Lemieux (2008). These estimates are given by obtaining linear fits locally, i.e. within some bandwidth h_x on either side of the cutoff C:

$$\min_{\alpha_l,\beta_l} \sum_{i:X_i\in(C-h_x,C)} (Y_i - \alpha_l - \beta_l(X_i - C))^2 \quad \text{and} \quad \min_{\alpha_r,\beta_r} \sum_{i:X_i\in[C,C+h_x)} (Y_i - \alpha_r - \beta_r(X_i - C))^2$$

For each courthouse pair, we then estimate τ_C as:

$$\hat{\tau}_C = \hat{\alpha}_r - \hat{\alpha}_l$$

An important consideration here is the bandwidth selection procedure. We present the LATE estimates for many possible bandwidth choices up to some distance from the boundary (e.g. up to 5km from the boundary). We also give the robust point estimates and CIs from the bandwidth selection procedure used by the `rdrobust` package (Calonico et al. (2023) for details).

To estimate the CLATE ($\tau_C(z)$), we again use a local linear estimator. We define a grid of different bandwidths for the X and Z variables, denoted h_x and h_z, respectively. We then obtain two local linear fits for each bandwidth pair (h_x, h_z) to estimate $\mathbb{E}(Y_1|X = C, Z = z)$ and $\mathbb{E}(Y_0|X = C, Z = z)$, resp., as follows:

$$\min_{\alpha_l,\beta_l,\gamma_l} \sum_{i:X_i\in(C-h_x,C) \text{ and } Z_i\in(z-h_z,z+h_z)} (Y_i - \alpha_l - \beta_l(X_i - C) - \gamma_l(Z_i - z))^2$$

$$\min_{\alpha_r,\beta_r,\gamma_r} \sum_{i:X_i\in[C,C+h_x) \text{ and } Z_i\in(z-h_z,z+h_z)} (Y_i - \alpha_r - \beta_r(X_i - C) - \gamma_r(Z_i - z))^2$$

For each courthouse boundary C and bandwidth pair (h_x, h_z), we then estimate $\tau_C(z)$ as:

$$\hat{\tau}_C(z) = \hat{\alpha}_r - \hat{\alpha}_l$$

Because we estimate $\tau_C(z)$ for many combinations of the X and Z bandwidths (i.e. (h_x, h_z) pairs) (h_x) and Z bandwidth (h_z), we then average across these estimates (using uniform weights) to obtain our CLATE estimates.[29] We show in Appendix G how the "bandwidth averaging" procedure recovers $\tau_C(z)$ and can perform as well as cross-validation bandwidth selection procedures. We also present the `np` cross-validated CLATE estimates in Appendix J.

[29] Averaging different kernel-based estimators is explored, e.g., in Chernova et al. (2020).

4.2 Unconditional Cutoff Effects: Estimating the LATEs

For each courthouse pair, we begin by considering only cases close to the boundary. To estimate the LATE at the courthouse boundaries, we consider only cases within a 5km buffer zone around the boundary. The cases we consider for Pasadena and West Covina, e.g., are shown in Figure 4.

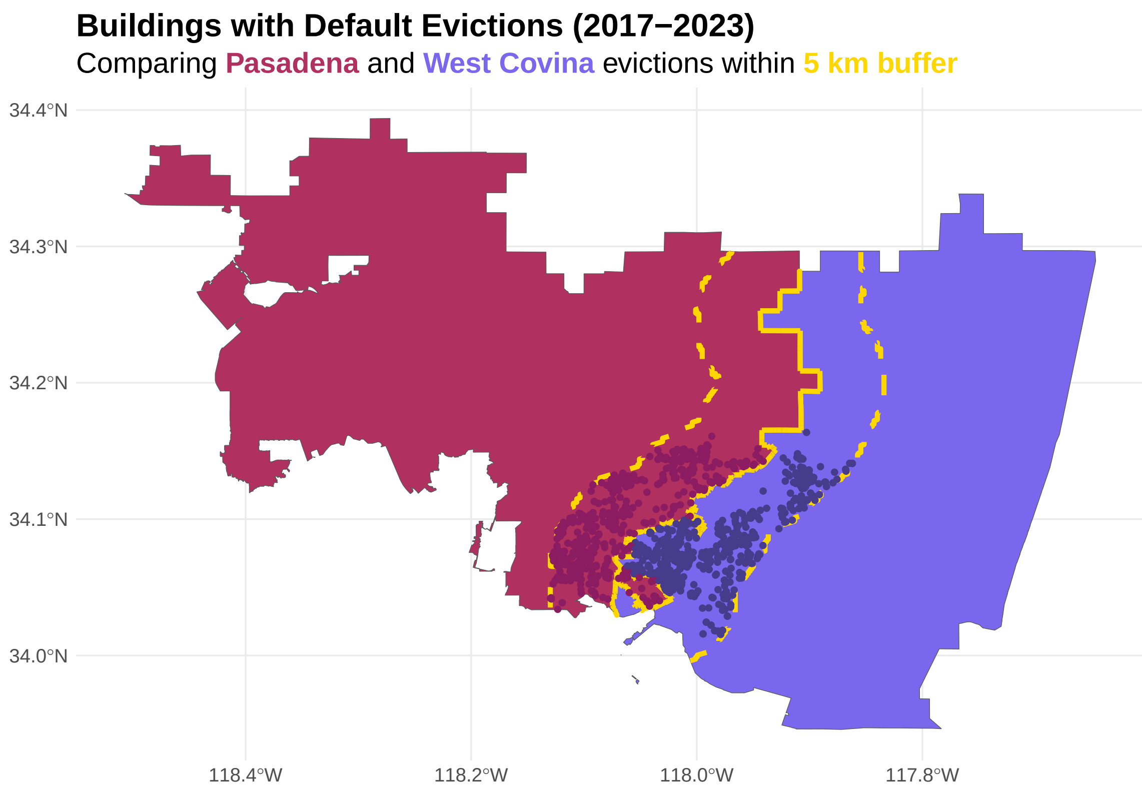
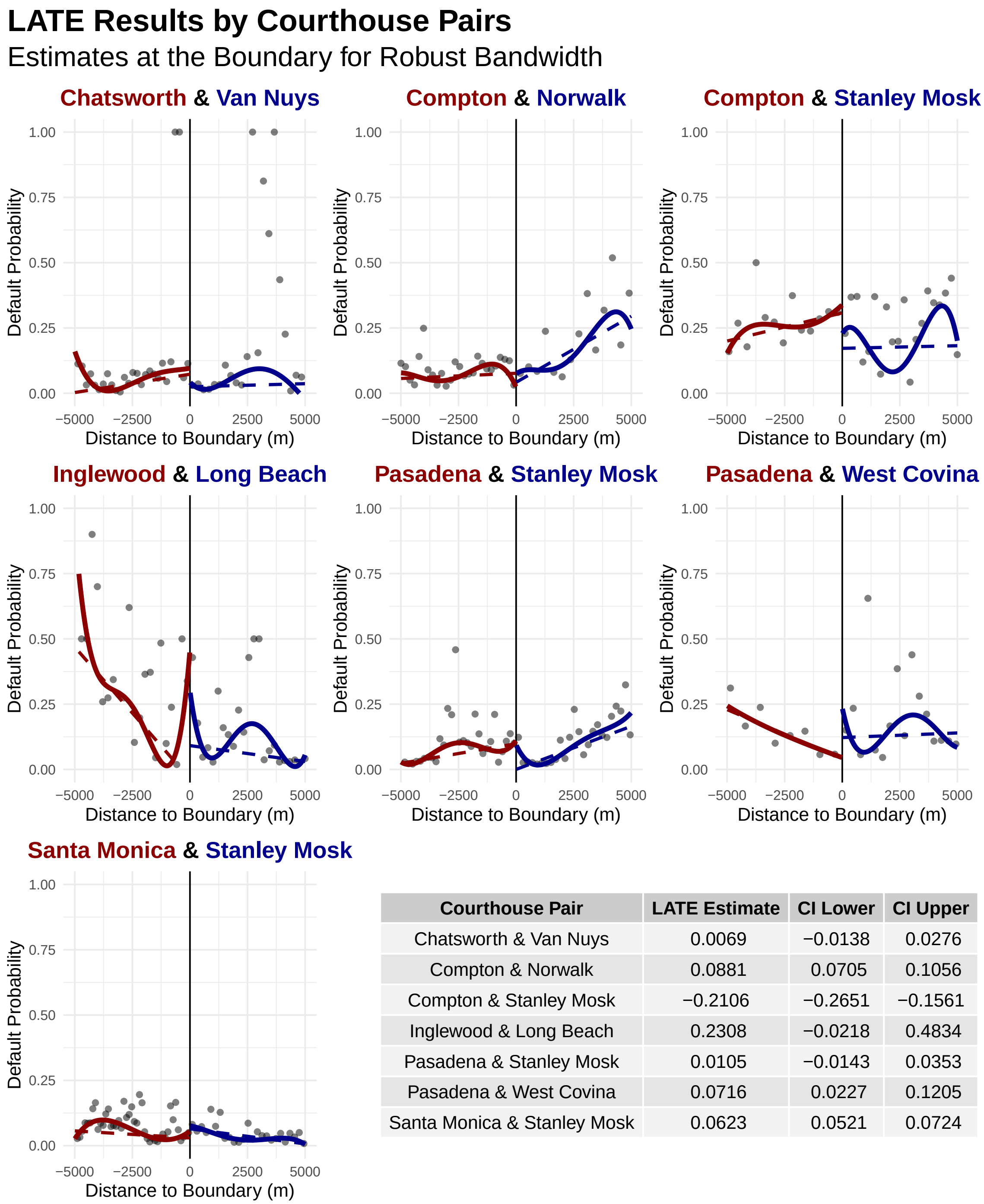


Figure 4. Pasadena & West Covina Map
Note: The observed default addresses within 5km of the Pasadena and West Covina courthouse boundary are plotted as points.

Our estimates for the LATE at different courthouse boundaries C

$$\tau_C = \mathbb{E}(Y_1 - Y_0 | X = C)$$

are presented below. In Figure 5, we plot the LATE estimates from the robust bandwidth selection procedure in Calonico et al. (2014) using companion software Calonico et al. (2015).



Courthouse Pair	LATE Estimate	CI Lower	CI Upper
Chatsworth & Van Nuys	0.0069	−0.0138	0.0276
Compton & Norwalk	0.0881	0.0705	0.1056
Compton & Stanley Mosk	−0.2106	−0.2651	−0.1561
Inglewood & Long Beach	0.2308	−0.0218	0.4834
Pasadena & Stanley Mosk	0.0105	−0.0143	0.0353
Pasadena & West Covina	0.0716	0.0227	0.1205
Santa Monica & Stanley Mosk	0.0623	0.0521	0.0724

Figure 5. LATE Estimates by Courthouse Pair (`rdrobust`)

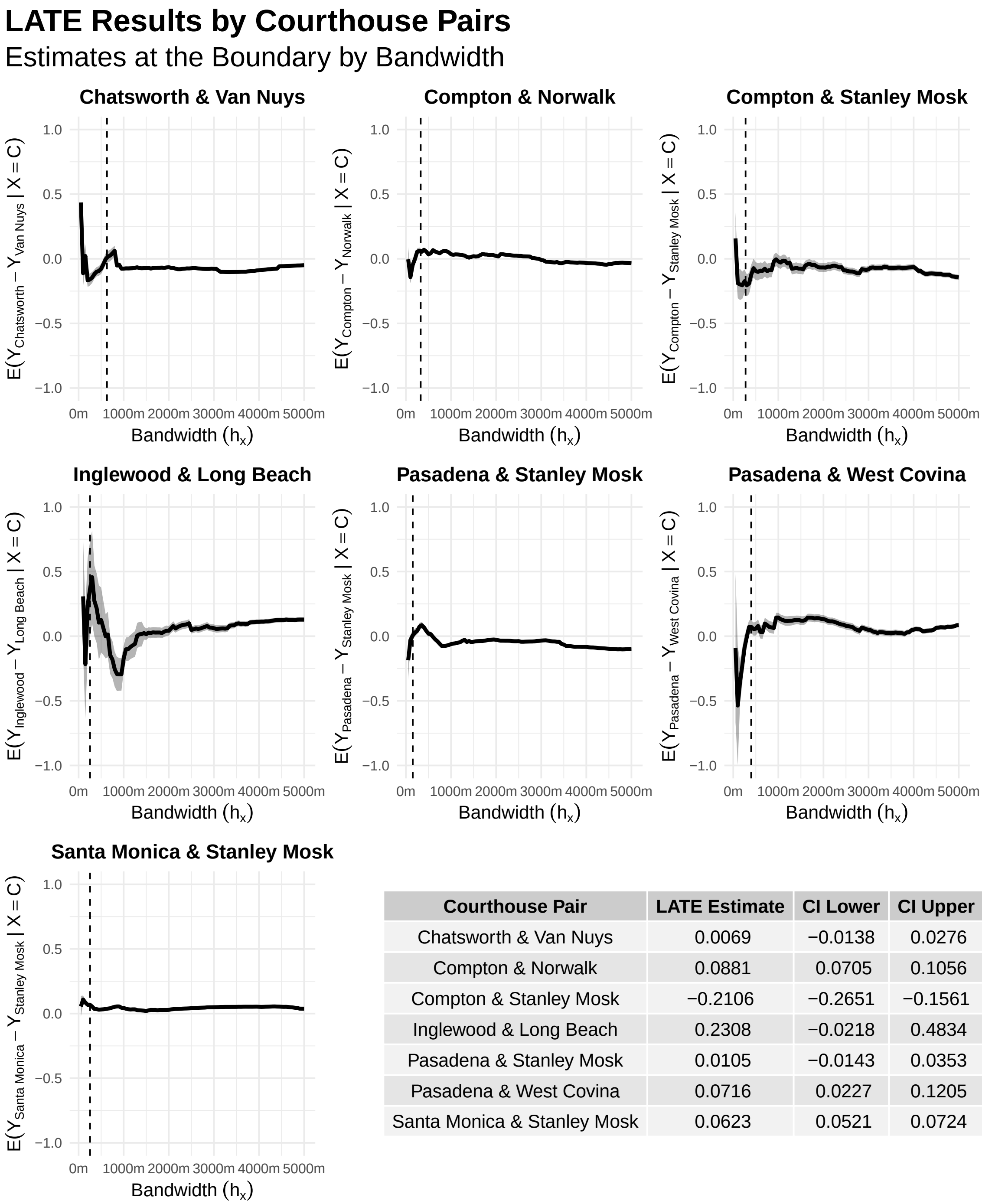
Note: The LATE estimates ($\hat{\tau}_C$) at each courthouse pair boundary using the optimal bandwidth selection procedure in the `rdrobust` package (Calonico et al., 2023). The default quartic polynomial (solid line) and linear (dashed line) fits are plotted for each courthouse separately. The gray points are evenly-spaced binned means using the `rdplot()` function. The robust point estimates are reported (with robust CIs) in the table for each courthouse pair.

The robust estimates are plotted in each courthouse panel and are also given in table form in Figure 5. The robust estimates range from 0.7–23.1 percentage points. In three courthouse pairs, the robust LATE estimate is not significant: Chatsworth & Van Nuys, Inglewood & Long Beach, and Pasadena & Stanley Mosk. In the remaining four pairs, the robust LATE estimate is significant but varies in size. The smallest significant effect is 6.23 percentage points (Santa Monica & Stanley Mosk), whereas the largest significant effect is -21.06 percentage points (Compton & Stanley Mosk).

Because eviction records are sensitive legal documents, they do not contain much individual information on landlords and tenants. Without such information (e.g. tenant demographics, tenant monthly rent, tenant income), it is difficult to directly assess covariate balance near the courthouse pair boundaries. We therefore rely on building- and neighborhood-level covariates to assess the validity of the discontinuity design. Specifically, we look for balance in pre-determined building and neighborhood covariates using the `rdrobust` optimal bandwidth. We use data on property value from the LA County Assessor and imputed median rent data from the ACS.

We show covariate means for records within the optimal bandwidth from the courthouse pair boundary in Appendix I. We find that some courthouse pairs are better balanced than others. For the courthouse pair where we find the largest effect (Compton & Stanley Mosk), we find no significant building and neighborhood level covariate imbalances. However, for the Compton & Norwalk pair, we reject balance for all four covariates: year building built, total property value, taxable property value, and imputed median building rent. Note also that the balance tables compare cases across the entire courthouse pair boundary, so that some imbalance likely comes from the spatial data and the spatial comparison. See Appendix I for more details.

Finally, we test the sensitivity of the LATE estimates to the bandwidth parameter. In Figure 6, we plot the local linear LATE estimates as a function of the bandwidth h_x. For example, we see large differences in magnitude and sign for the Inglewood & Long Beach LATE estimate as we decrease the bandwidth from 5000 meters to 0 meters. On the other hand, some of the LATE estimates are highly robust to the selected bandwidth. For example, the Santa Monica & Stanley Mosk LATE estimates are positive and roughly constant across bandwidths h_x.



Courthouse Pair	LATE Estimate	CI Lower	CI Upper
Chatsworth & Van Nuys	0.0069	−0.0138	0.0276
Compton & Norwalk	0.0881	0.0705	0.1056
Compton & Stanley Mosk	−0.2106	−0.2651	−0.1561
Inglewood & Long Beach	0.2308	−0.0218	0.4834
Pasadena & Stanley Mosk	0.0105	−0.0143	0.0353
Pasadena & West Covina	0.0716	0.0227	0.1205
Santa Monica & Stanley Mosk	0.0623	0.0521	0.0724

Figure 6. LATE Estimates by Courthouse Pair

Note: The LATE estimates ($\hat{\tau}_C$) at each courthouse pair boundary C are plotted as a function of bandwidth h_x. For each bandwidth h_x, the local linear estimate is plotted along with the CIs (gray ribbon). The table again gives the `rdrobust` package estimates of the LATE, along with the robust CIs. The dashed vertical line is the `rdrobust` optimal bandwidth.

4.3 Heterogeneous Conditional Effects: Distance-to-Court CLATEs

Next, we investigate potentially heterogeneous effects near the boundary. Specifically, we estimate the conditional local average treatment effect as a function of distance-to-court z. Recall the estimands are of the following form:

$$\tau_C(z) = \mathbb{E}(Y_1 - Y_0 | X = C, Z = z)$$

These are the local (i.e. at the cutoff $X = C$) average treatment effects conditional on the distance to assigned court being z. The idea is to compare only cases near the boundary that are the same distance (z) to the assigned court, whereas the LATE estimates above do not condition or control for distance to assigned court explicitly.

Our estimates for the same seven courthouse pairs are given in Figure 7. The average estimates across bandwidths is plotted in black for each courthouse pair. The blue and red bands are the 90% and 95% quantiles across bandwidths (h_x, h_z). The CLATE bandwidth-averaged estimates (black line) are a non-constant function of distance to court z and differ significantly between courthouse pairs.[30]

The CLATE estimates suggest there is considerable treatment effect heterogeneity along the distance-to-court dimension. For example, the Compton & Stanley Mosk CLATE estimates are positive for small z-values and negative for large z-values (downward-sloping). This suggests some renter sub-populations at different distances to court experience stronger or weaker courthouse assignment treatment effects.

The CLATE estimates are, in general, sensitive to the selected bandwidth. For most courthouse pairs, the 90% and 95% bandwidth quantiles do not pin down the sign of the effect but for a small number of z-values. The magnitude is also highly variable for most courthouse pairs and z-values. These issues are partially due to the small sample sizes that result from conditioning on a second variable (Z). The CLATE estimates should, therefore, be interpreted with some care.

The results are largely consistent with distance-to-court being an important factor affecting the default probability, as in Hoffman and Strezhnev (2023). For most courthouse pairs at almost all z-values, the bandwidth 90% and 95% quantiles contain zero. After controlling for distance-to-court z, in other words, there may be no further direct effect of court assignment on the default eviction probability because the bands contains zero. However, note that for two pairs (Pasadena & Stanley Mosk and Santa Monica & Stanley Mosk) the CLATE estimates do not include zero for some z-values.

[30] See also Appendix J for the `np` package CLATE estimates with cross-validated bandwidths.

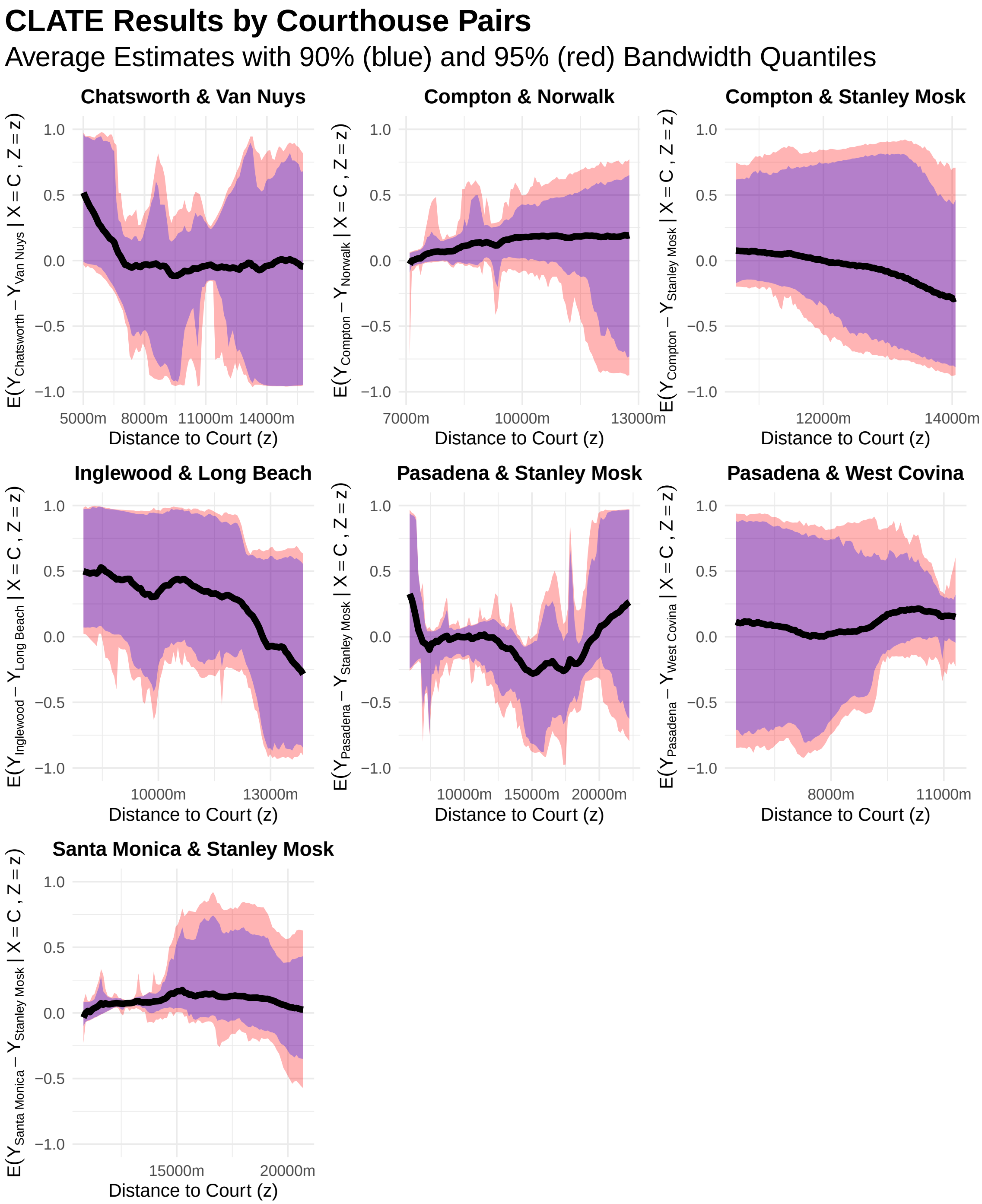


Figure 7. CLATE Estimates by Courthouse Pair

Note: The CLATE estimates $\hat{\tau}_C(z)$ are given as a function of distance-to-court z (in meters). For each distance z, the local linear estimator is averaged across 10000 bandwidth pairs (h_x, h_z). The 90% (blue) and 95% (red) bandwidth estimate quantiles are given for each z.

5 Conclusion

This paper extends research on the relationship between individual-level characteristics and eviction outcomes by exploring the mundane, yet complex institutional-level processes shaping the likelihood of tenant default in the Los Angeles Superior Court system. We find that case assignment—an institutionalized and automated process relying on the drawing of arbitrary boundaries—disadvantages tenants living along the margins of jurisdictional boundaries. Indeed, in our regression discontinuity design, we show there are significant and robust gaps in the local average eviction default probability across the boundaries for different courthouse regions.

This means that some tenants living in marginal areas are more likely than other tenants to default. Unlike the single-courthouse system in Philadelphia (Hoffman and Strezhnev, 2023), the institutional geography of eviction case processing in Los Angeles involves assigning cases into regional courthouses across a large metropolitan county. Since a default judgment occurs at the beginning of the eviction process, these cases represent a procedural injustice wherein tenants lose the cases against them (and their homes) before they have an opportunity to defend themselves in court. Thus, for tenant facing eviction, one's likelihood of losing their case and home, and potentially experiencing homelessness, is a function of factors that differ from the demographic and individual cultural variables tested in much of the literature.

The multi-faceted nature of eviction institutions makes welfare-improving legal reform difficult, particularly in big cities like Los Angeles. The impact of different levers in the eviction machine—assignment maps, court waiting times, legal defense resources, and procedures for dealing with court non-attendance—on tenants, landlords, and the rental market is poorly understood. Determining how to optimally pull these levers should be done *ceteris paribus* and in a data-driven manner.

By focusing on an institutional mechanism that increases the likelihood of experiencing default in eviction lawsuits, we have identified an area where modest reform could pay significant dividends in eviction prevention. A seemingly small intervention to redraw and optimize jurisdictional maps could decrease defaults and, by extension, procedural inequality in the civil justice system. The court assignment policy lever can complement other policies, like creating tenant protections to keep tenants housed and expanding tenants' access to attorneys. This multi-pronged policy approach toward eviction cases could help mitigate the devastating consequences of LA County's affordable housing and homelessness crises.

References

A. Baird. Right to counsel in eviction cases: A california case study, 2021. URL https://sites.bu.edu/dome/2021/08/27/right-to-counsel-in-eviction-cases-a-california-case-study/.

S. Calonico, M. D. Cattaneo, and R. Titiunik. Robust nonparametric confidence intervals for regression-discontinuity designs. *Econometrica*, 82(6):2295–2326, 2014.

S. Calonico, M. D. Cattaneo, and R. Titiunik. rdrobust: An r package for robust nonparametric inference in regression-discontinuity designs. *R Journal*, 7(1):38–51, 2015.

S. Calonico, M. D. Cattaneo, M. H. Farrell, and R. Titiunik. *rdrobust: Robust Data-Driven Statistical Inference in Regression-Discontinuity Designs*, 2023. URL https://CRAN.R-project.org/package=rdrobust. R package version 2.2.

O. Chernova, F. Lavancier, and P. Rochet. Averaging of density kernel estimators. *Statistics and Probability Letters*, 158, 2020. doi: https://doi.org/10.1016/j.spl.2019.108645. URL https://www.sciencedirect.com/science/article/pii/S0167715219302913.

R. Collinson, J. E. Humphries, N. Mader, D. Reed, D. Tannenbaum, and W. Van Dijk. Eviction and poverty in american cities. *The Quarterly Journal of Economics*, 139 (1):57–120, 2024.

M. Desmond. *Evicted*. Penguin Books, 2017.

A. Gromis, I. Fellows, J. R. Hendrickson, L. Edmonds, L. Leung, A. Porton, and M. Desmond. Estimating eviction prevalence across the united states. *Princeton University Eviction Lab*, May 13 2022. URL https://data-downloads.evictionlab.org/#estimating-eviction-prevalance-across-us/.

T. Hayfield and J. S. Racine. *Nonparametric Econometrics: The np Package*, 2008. URL https://www.jstatsoft.org/index.php/jss/article/view/v027i05.

D. A. Hoffman and A. Strezhnev. Longer trips to court case evictions. *PNAS*, 120 (2), 2023.

G. W. Imbens and T. Lemieux. Regress discontinuity designs: A guide to practice. *Journal of Econometrics*, 142(2):615–635, 2008.

L. Kaplow. Rules versus standards: An economic analysis. *Duke Law Journal*, 42, 1992.

E. Larson. Case characteristics and defendant tenant default in a housing court. *Journal of Empirical Legal Studies*, 2006.

LASC. Civil fee schedule (public), 2024. URL https://lascpubstorage.blob.core.windows.net/cpw/LIBSVCExecutiveSupport-265-2024FeeSchedule010124.pdf.

D. S. Lee and T. Lemieux. Regression discontinuity designs in economics. *Journal of Economic Literature*, 48:281–355, June 2010.

M. C. Lens, K. Nelson, and A. Gromis. The neighborhood context of eviction in southern california. *City and Community*, 19(4):912–932, 2020.

L. Mayor. Mayor bass: Press release on sep. 19, 2023, 2023. URL https://mayor.lacity.gov/news/apply-now-mayor-bass-councilmember-raman-and-los-angeles-housing-department-announ

K. Nelson. The political determinants of access to justice. Unpublished, 2023.

K. Nelson, A. Gromis, Y. Kuai, and M. C. Lens. Spatial concentration and spillover: Eviction dynamics in neighborhoods of los angeles, california, 2005-2015. *Housing Policy Debate*, 31(3-5):670–695, 2021.

J. Prescott. Improving access to justice in state courts with platform technology. *Vanderbilt Law Review*, 70(6):1993–2050, 2017.

H. Wiley. Newsom signs tenant bills to lower security deposits, prevent more evictions, 2023. URL https://www.latimes.com/california/story/2023-10-11/newsom-tenant-protection-california-renters-eviction-security-deposits.

APPENDICES

A Appendix A: Creating the Courthouse Assignment Map

Appendix A discusses the creation of the courthouse assignment map and shapefiles.

As discussed in the main body of the paper, the filing rule for evictions is unique to eviction cases. Assignment to a court is determined by a neighborhood–zip pair. We started with zip-codes where the filing rule uniquely specifies a courthouse. Using zip code shapefiles from LA County geohub, this determines the courthouse assignment map for most of LA County. In the remaining zip codes where there are multiple eviction courthouses, we determined neighborhood boundaries within the zip code. We used other LA County geohub shapefiles—in particular, the census tract shapefiles—to determine neighborhoods within the remaining unassigned zip codes.

Next, if a particular neighborhood/city is always assigned to a particular courthouse (across all zip-codes), then we assigned the census tracts with those neighborhood/city names to that courthouse. We then manually created the courthouse assignment shapefiles for zip codes where assignment is done by a street divider. This involved using street and highway shapefiles from LA County and the Census shapefiles. Finally, for any remaining unassigned census tracts, we used the scraped eviction data from 2018 to determine where the vast majority of cases for that census tract are assigned. We assumed that the majority assigned courthouse was the correct one, i.e. we minimized classifying observed evictions as "misfiled."

Due to the complex governing structure of LA County, some of the city/neighborhoods listed in the official Zip Code Table are not official, incorporated governing regions. Therefore the precise boundaries of some city-zip pairs is difficult to ascertain. Fortunately, 89% (480 of 539) of the zip codes in the Zip Code Table are uniquely assigned to one courthouse. For example, in Table A1 the highlighted rows for 90006 show that both Koreatown and Los Angeles evictions are assigned to Stanley Mosk Courthouse.

Appendix Table A1. Simplifying Assignment: Unique Courthouses

Zip Code	City/Neighborhood	Modifier	Courthouse
90006	KOREATOWN		Stanley Mosk Courthouse
90006	LOS ANGELES		Stanley Mosk Courthouse
90007	LOS ANGELES		Stanley Mosk Courthouse
90008	BALDWIN HILLS		Stanley Mosk Courthouse
90008	CRENSHAW		Stanley Mosk Courthouse
90008	LIEMERT PARK		Stanley Mosk Courthouse
90008	LOS ANGELES		Santa Monica Courthouse

Accordingly, we work with a Simplified Zip Code Table that aggregates neighborhoods in the event that all neighborhoods within a zip code are assigned to one unique courthouse. For instance, Table A2 below highlights the Simplified Zip Code Table for the 90006 zip code.

Appendix Table A2. Simplified Zip Code Table

Zip Code	City/Neighborhood	Modifier	Courthouse
90006	KOREATOWN-LOS ANGELES		Stanley Mosk Courthouse
90007	LOS ANGELES		Stanley Mosk Courthouse
90008	BALDWIN HILLS		Stanley Mosk Courthouse
90008	CRENSHAW		Stanley Mosk Courthouse
90008	LIEMERT PARK		Stanley Mosk Courthouse
90008	LOS ANGELES		Santa Monica Courthouse

Using the Simplified Zip Code Table and the official LA County Zip Codes shapefiles, we are able to unambiguously determine where the vast majority of eviction cases in Los Angeles County must be filed. For the remaining zip codes—where eviction cases are assigned by neighborhood or location relative to a street to different courthouses—we determine the contours of particular neighborhood-zip code pairs using official shapefiles from the LA County eGIS Program.

We then checked the map against eviction records. If a neighborhood-zip code pair had a majority of filed cases with observed courthouses that did not match the courthouse we specified originally for the region, then we corrected that region's filing courthouse. Even after incorporating this correction into the courthouse filing map, approximately 2% of cases (2018, 2019, and 2023) have observed filing courthouses that do not match the "true" filing courthouse for that region. See Section 3 above and Appendix H for misfiling discussion.

B Appendix B: Docket Records (Scraping the LASC Portal, Sampling Rates, Geocoding Addresses)

Appendix B describes how the docket record data was obtained. We obtained docket records from scraping the LA Superior Court public case portal. Because court filing number is determined by YEAR-COURT LOCATION-CASE TYPE-NUMBER formats, we are able to scrape every number up to the total number of records, which we know from FOIA requests. In general, we added a search buffer in case the FOIA volume data was slightly off. Because the records themselves have dates, we check that the final docket we find is close to "12-31-YEAR". In unlawful detainer cases, this means that case numbers look like:

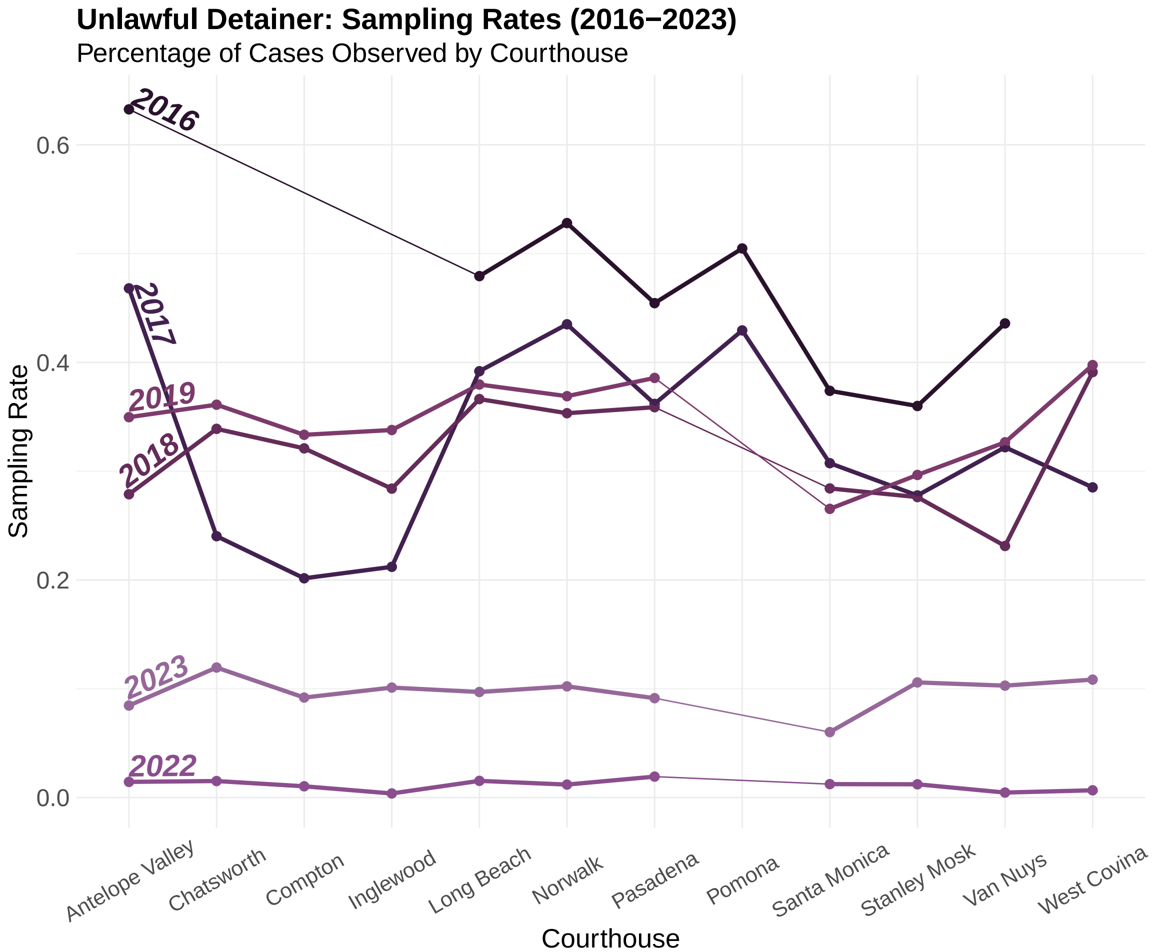
$$\overbrace{17}^{\text{year}}\underbrace{\text{PD}}_{\text{court}}\overbrace{\text{UD}}^{\text{type}}\underbrace{00001}_{\text{filing number}}$$

which is a 2017 Pasadena courthouse unlawful detainer (UD) case with filing number 00001.

Over time, the filing formats changed, which are recorded by local court rules. Changes to sealing records rules changed too, effective Jan. 1, 2017. See local rules of court for information on the filing numbers and sealing laws.

B.1 Default Evictions Sampling Rates

Appendix B.1 describes sampling rates from the FOIA total filing numbers and the number of defaults we observe. Note that data collection carried out in Nov. 2023. Here are sampling rates:



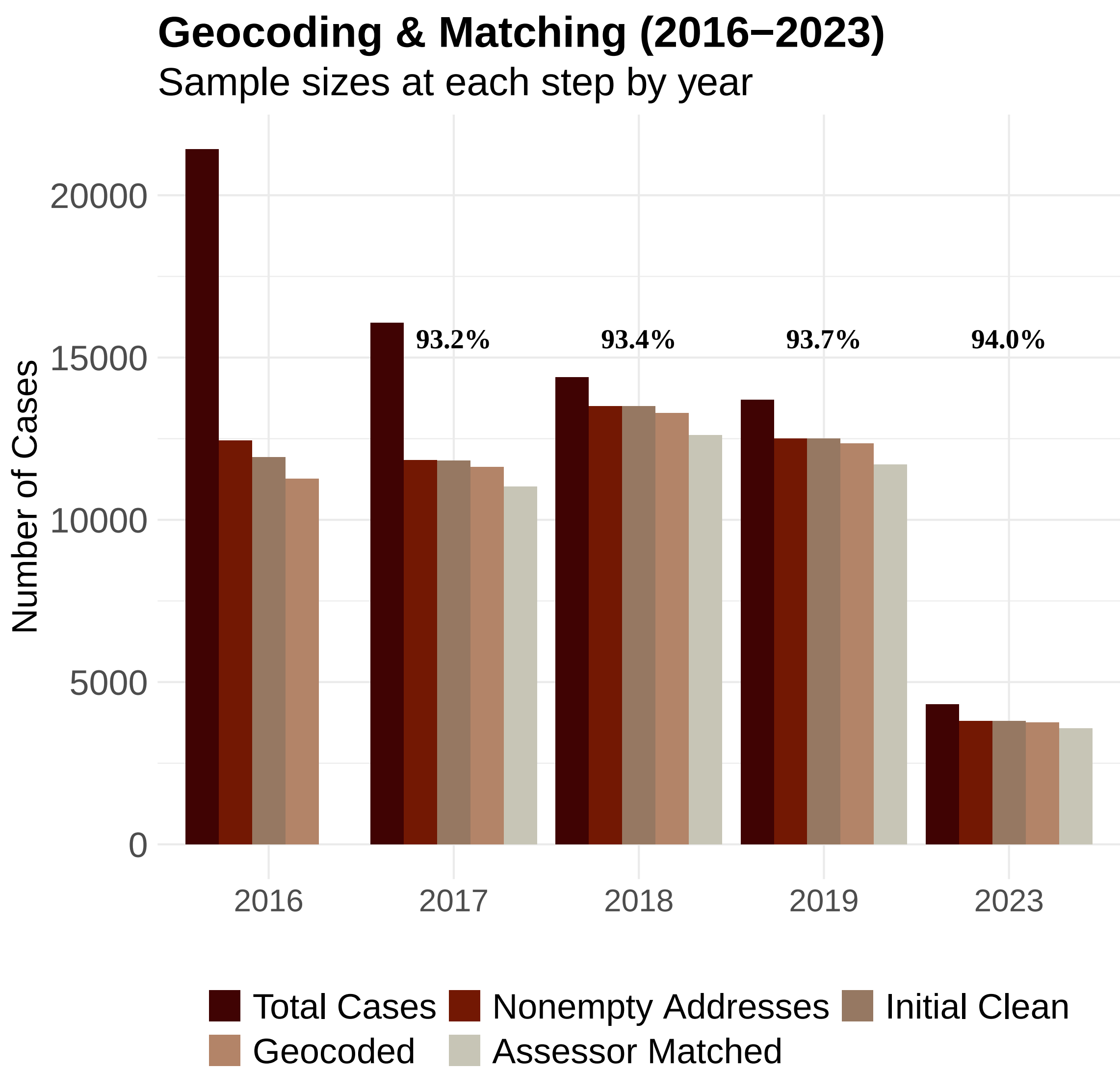
Appendix Figure B1. Sampling Rates: 2016-2023

Since most of the observed cases are default judgments, the sampling rate is essentially the default judgment rate at each courthouse for each year. Note also that the denominators are the higher of either the FOIA number reported to us by LASC or the last scraped case number, in cases of disagreement.

B.2 Geocoding the Addresses

The number of records observed at each step of the geocoding process are displayed in Figure B2. The percentages at the top of each year grouping give the proportion of eviction records matched in the final step to assessor data out from the set of eviction records that contain a nonempty address. In the process of cleaning, geocoding, and matching to assessor information we do not lose many cases.[31]

[31]Note that the assessor match for the 2016 year is omitted because it is not part of the primary analysis. As discussed above, there was a different courthouse assignment rule in 2016.



Note: The geocoded numbers are for "High" or "Exact" matches only from Mapbox API. The percentages are number of assessor matched cases divided by number of cases with nonempty address.

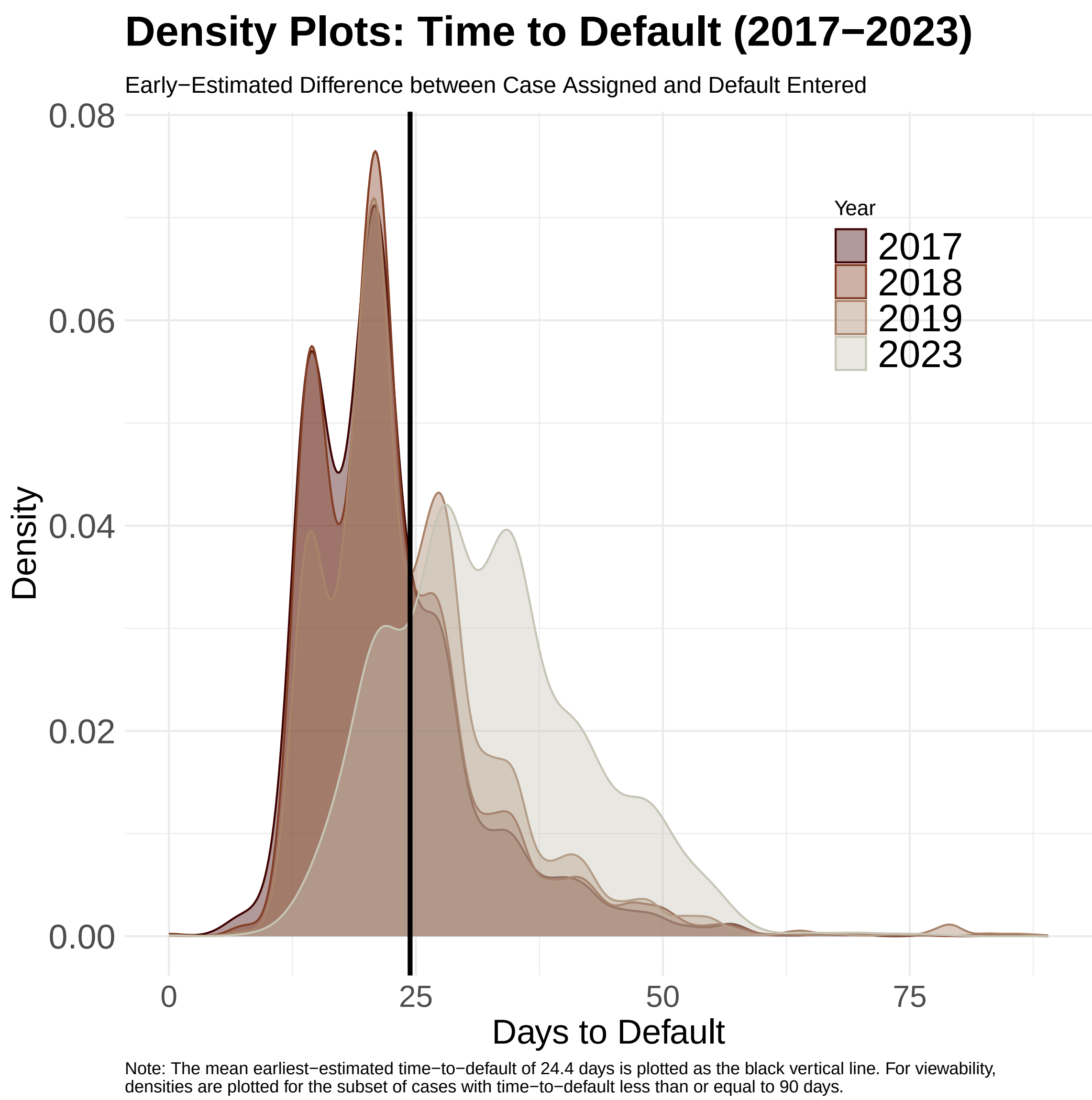
Appendix Figure B2

C Appendix C: Time-to-Default Plots

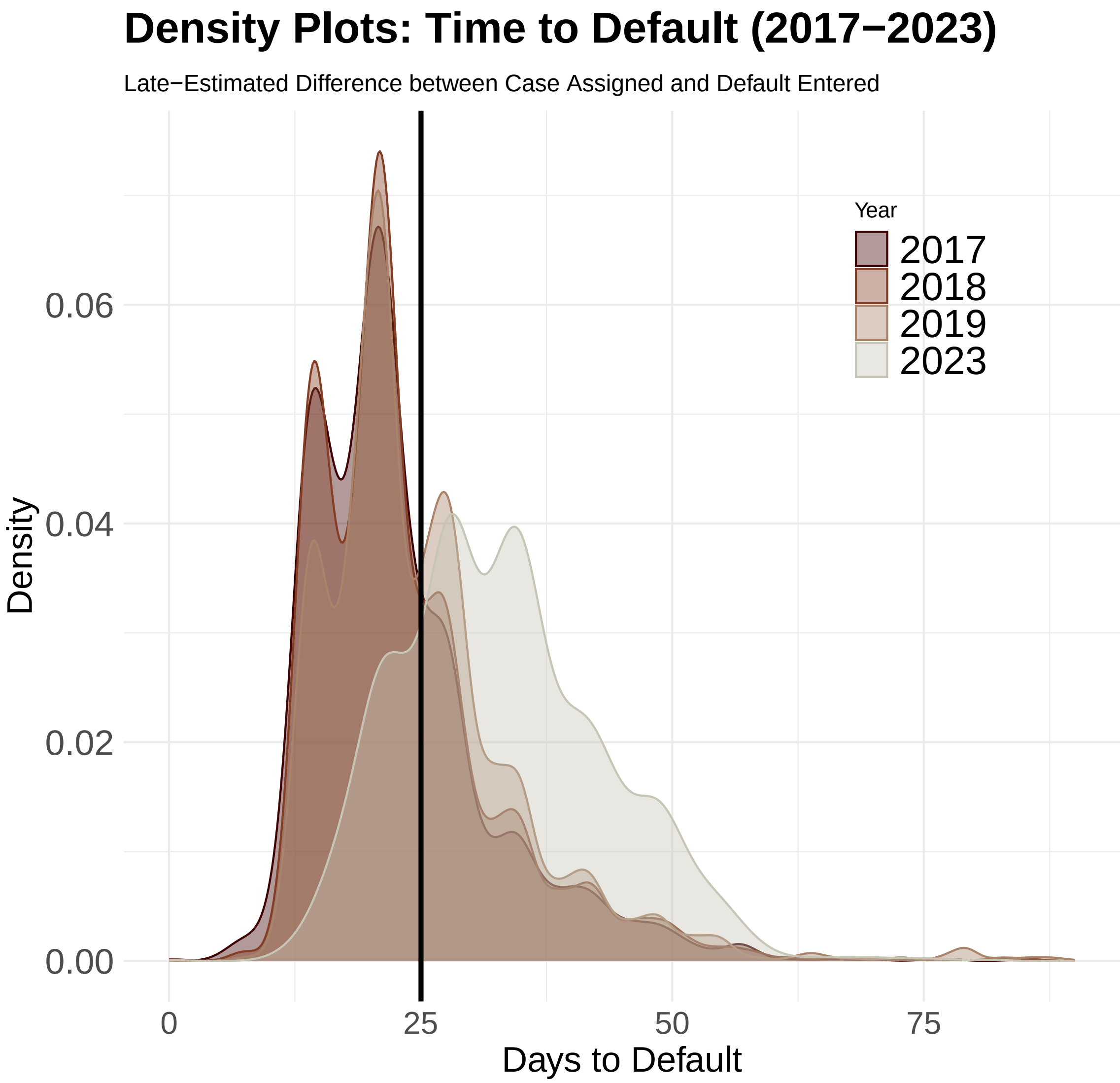
Appendix C contains additional plots documenting how long it takes for the default cases to reach default status.

We calculate the number of days to default status using regular expressions on the raw docket data. We extract three dates from the raw case data: the case start-date (measured as the date on the docket the case is assigned to a judge), the earliest possible default entry date (measured as the first appearance of "C.C.P. 415.46" or "C.C.P. 1169" on the docket), and the latest possible default entry date (measured as the last appearance of "C.C.P. 415.46" or "C.C.P. 1169" on the docket).[32] In some (but not many) cases, the last appearance of a default entry differs from the first default entry date. This makes only a small difference in the mean across all years and courthouses: the early-estimated average time-to-default is 24.4 days versus the late-estimated average time-to-default of 25.0 days.

[32]To cast a wide net, the regex search is for the dates where either "415.46" or "1169" appear.



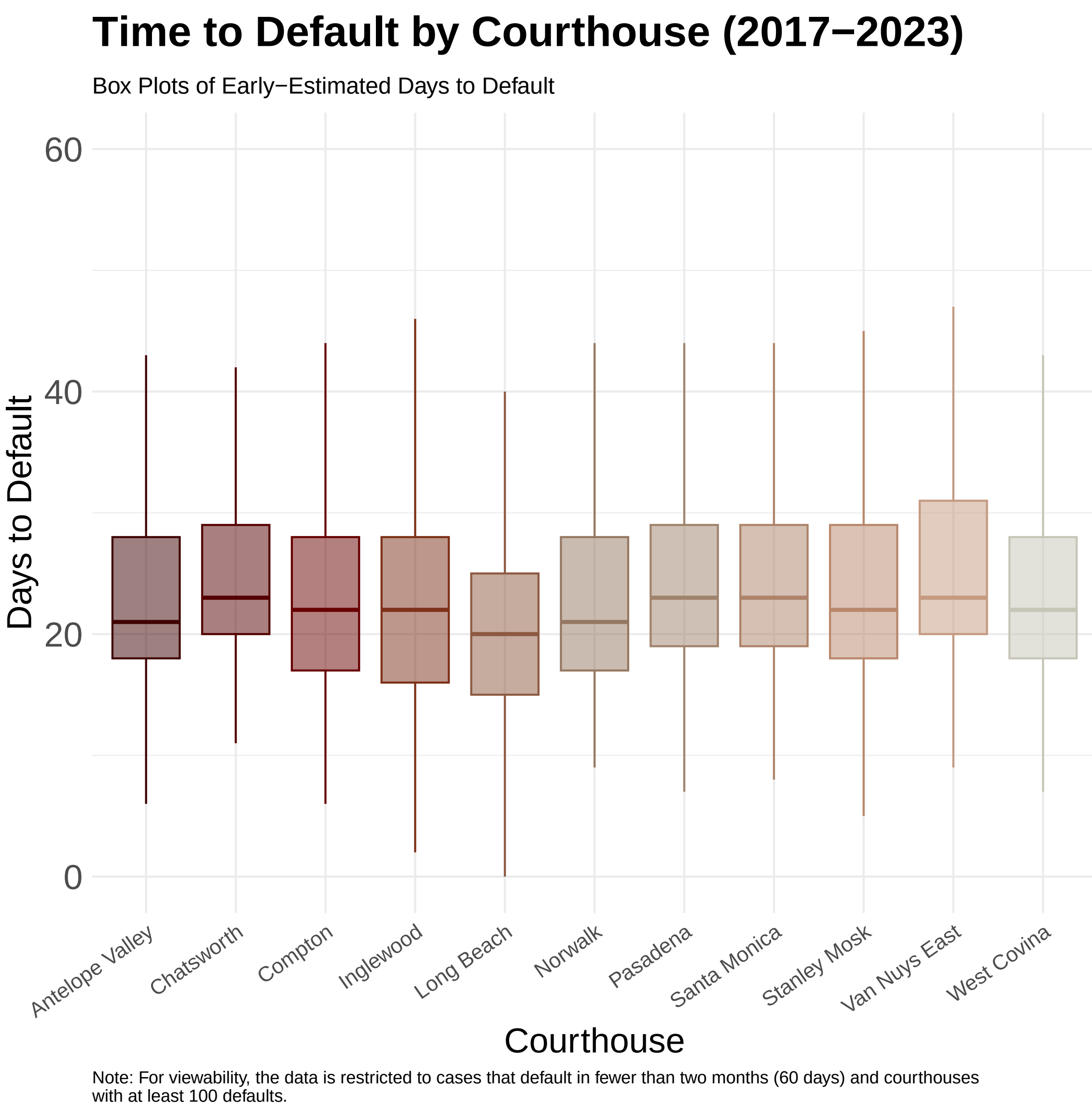
Appendix Figure C1. Time-to-Default: Early-Estimated Default Entered Date



Note: The mean earliest−estimated time−to−default of 25.0 days is plotted as the black vertical line. For viewability, densities are plotted for the subset of cases with time−to−default less than or equal to 90 days.

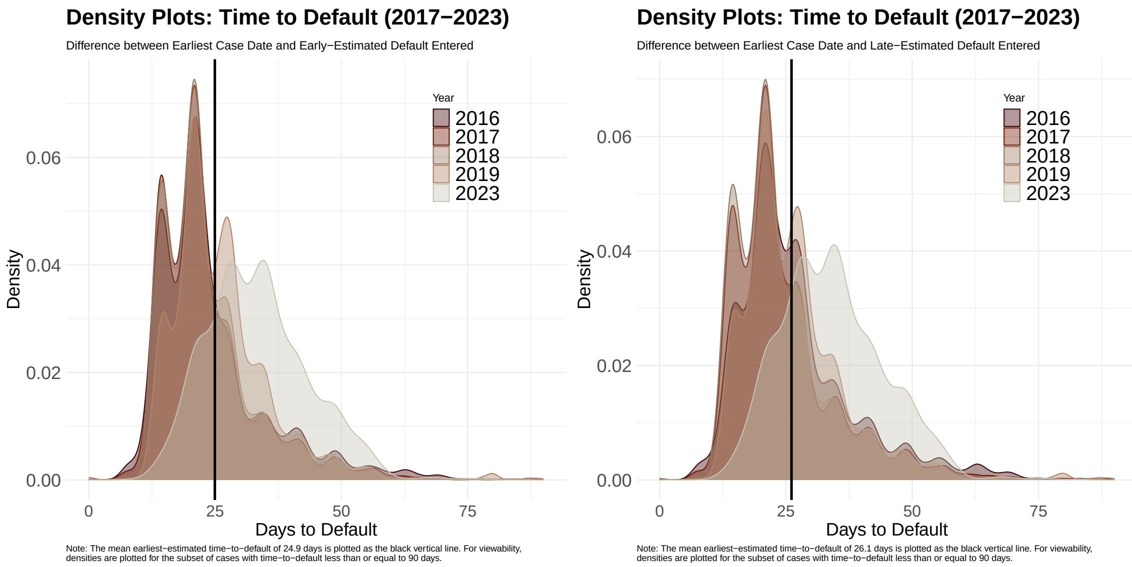
Appendix Figure C2. Time-to-Default: Late-Estimated Default Entered Date

We also record the box plots of the early-estimated time-to-default below for each courthouse pooled across all years: although there is variation across courthouses, the median time-to-default is similar for the 2017-2023 years.



Appendix Figure C3. Time-to-Default: By Courthouses

Alternatively, we can estimate the start date by the earliest date that appears within the docket. Then we can compute the difference in days between this start date and the estimated default date (early or late). The plots below in Figure C4 give densities for estimated time-to-default under this different way to measure the start date: the new mean estimated times to default are 24.9 days (early estimated default date) and 26.1 days (late estimated default date).

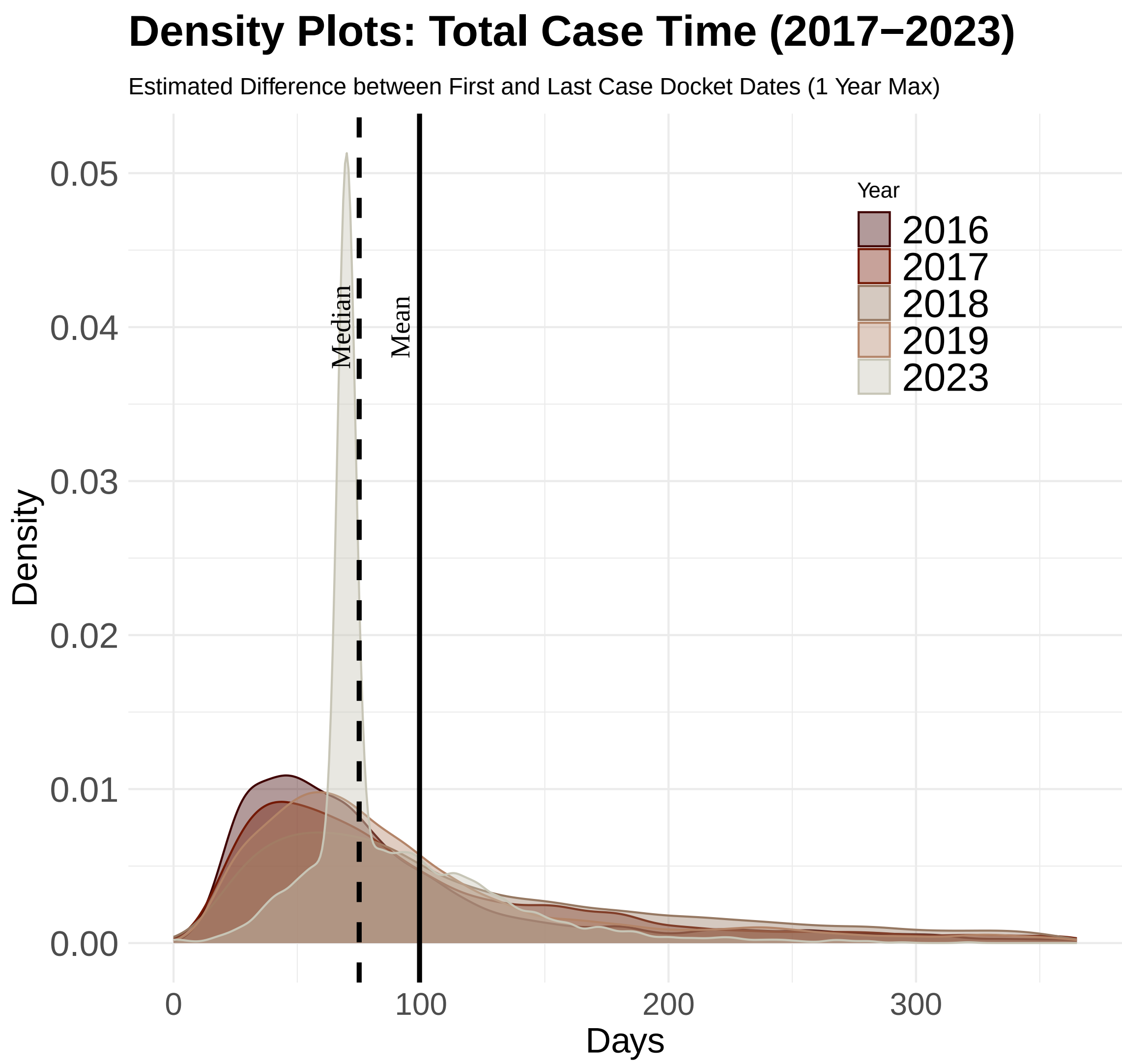


Appendix Figure C4. Time-to-Default: Using Earliest Case Dates

D Appendix D: Total Case Time Plots

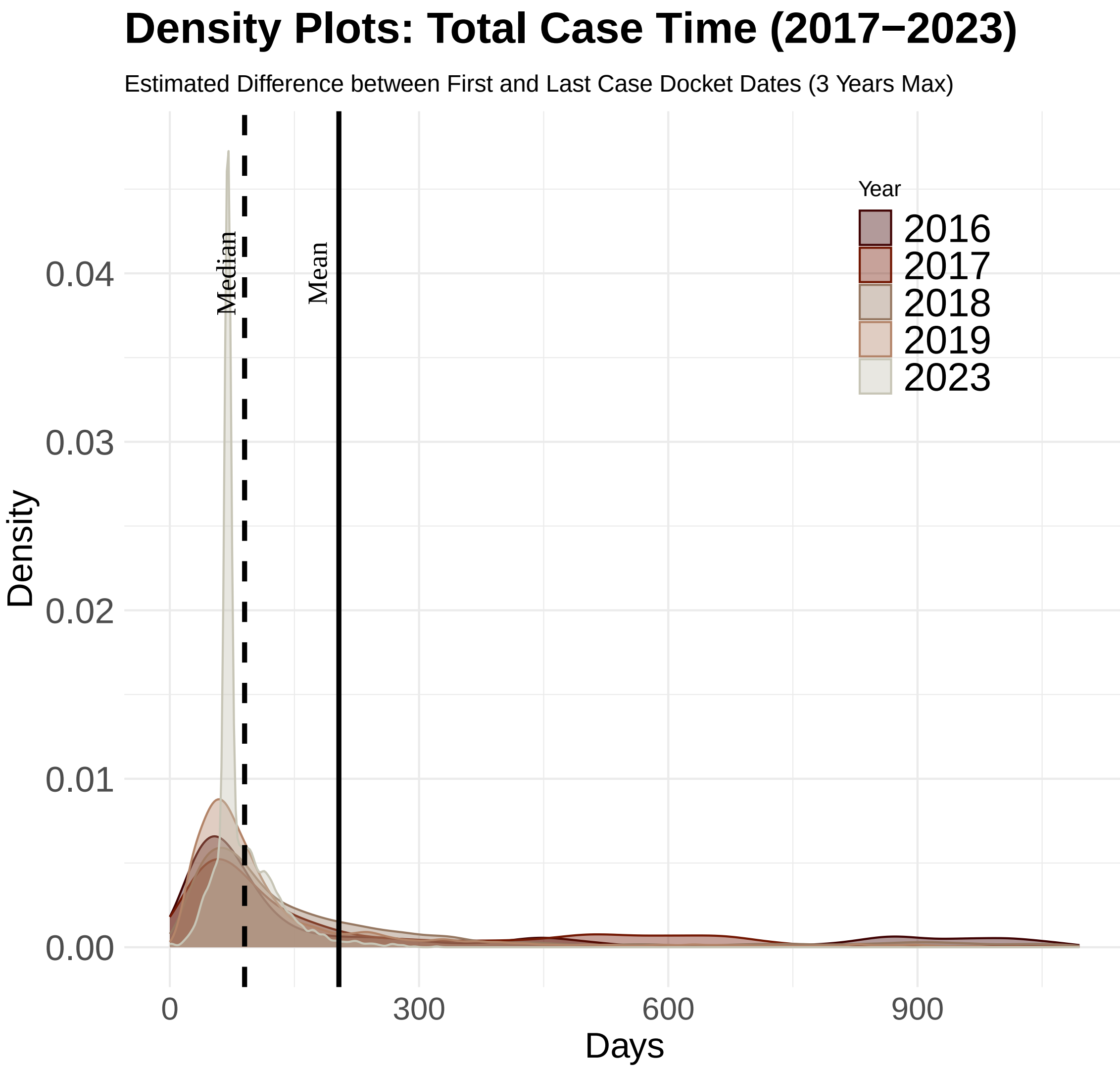
Appendix D contains plots on total case times. We extract all dates in the format Month/Day/Year (e.g. "01/01/2018") from the raw docket data, order the dates, and take the earliest and latest dates. The total time is the difference between the latest and earliest dates in the docket data for a given eviction case.

The two plots below contain the density plots for the subset of cases that are finished within 1 year or 3 years, respectively.



Note: The mean case time (99.4 days) and the median case time (75 days) are plotted as the black vertical solid and dashed lines, respectively. For viewability, densities are plotted for the subset of cases with case times than or equal to one year.

Appendix Figure D1

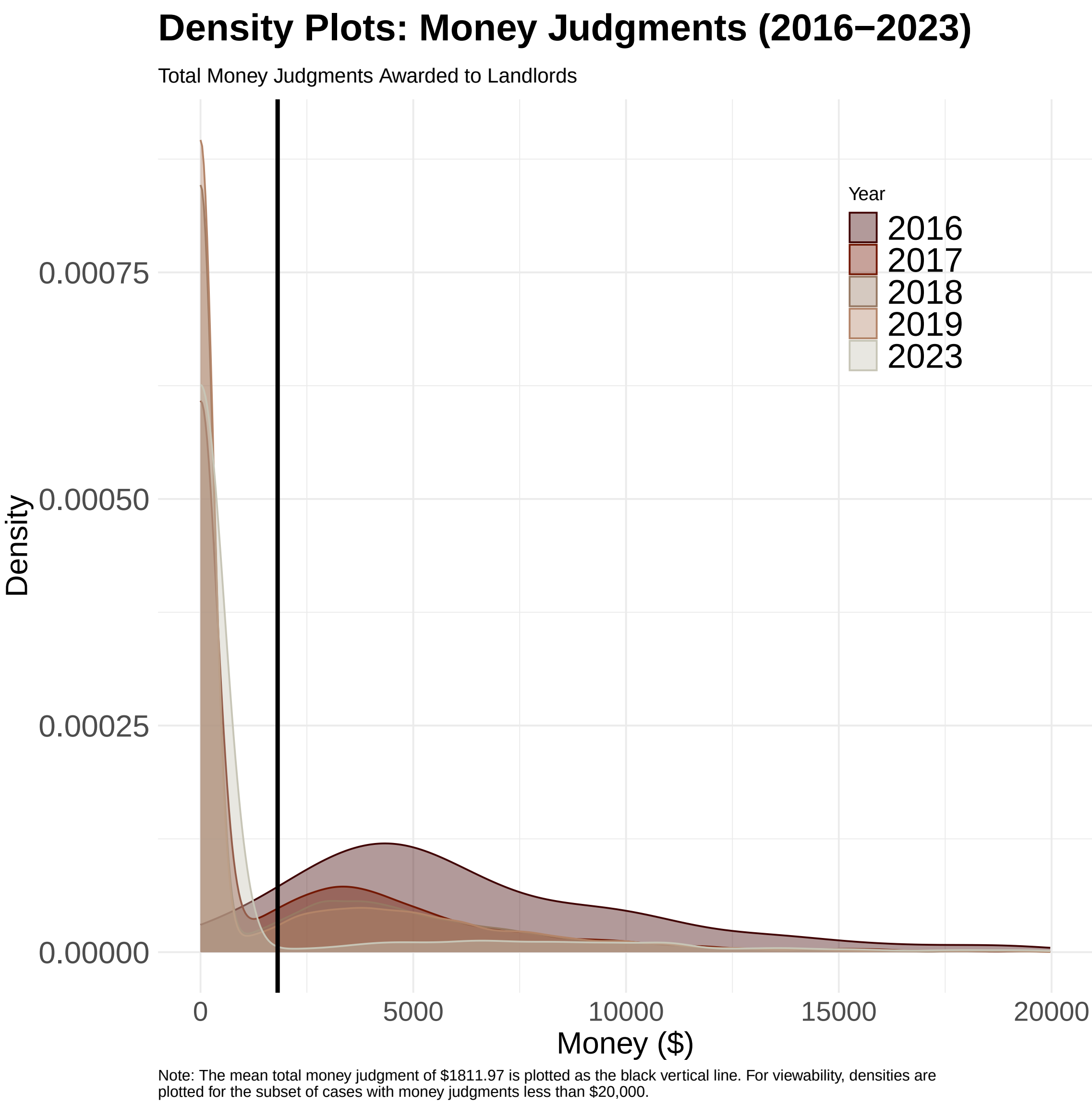


Note: The mean case time (203.5 days) and the median case time (90 days) are plotted as the black vertical solid and dashed lines, respectively. For viewability, densities are plotted for the subset of cases with case times than or equal to three years.

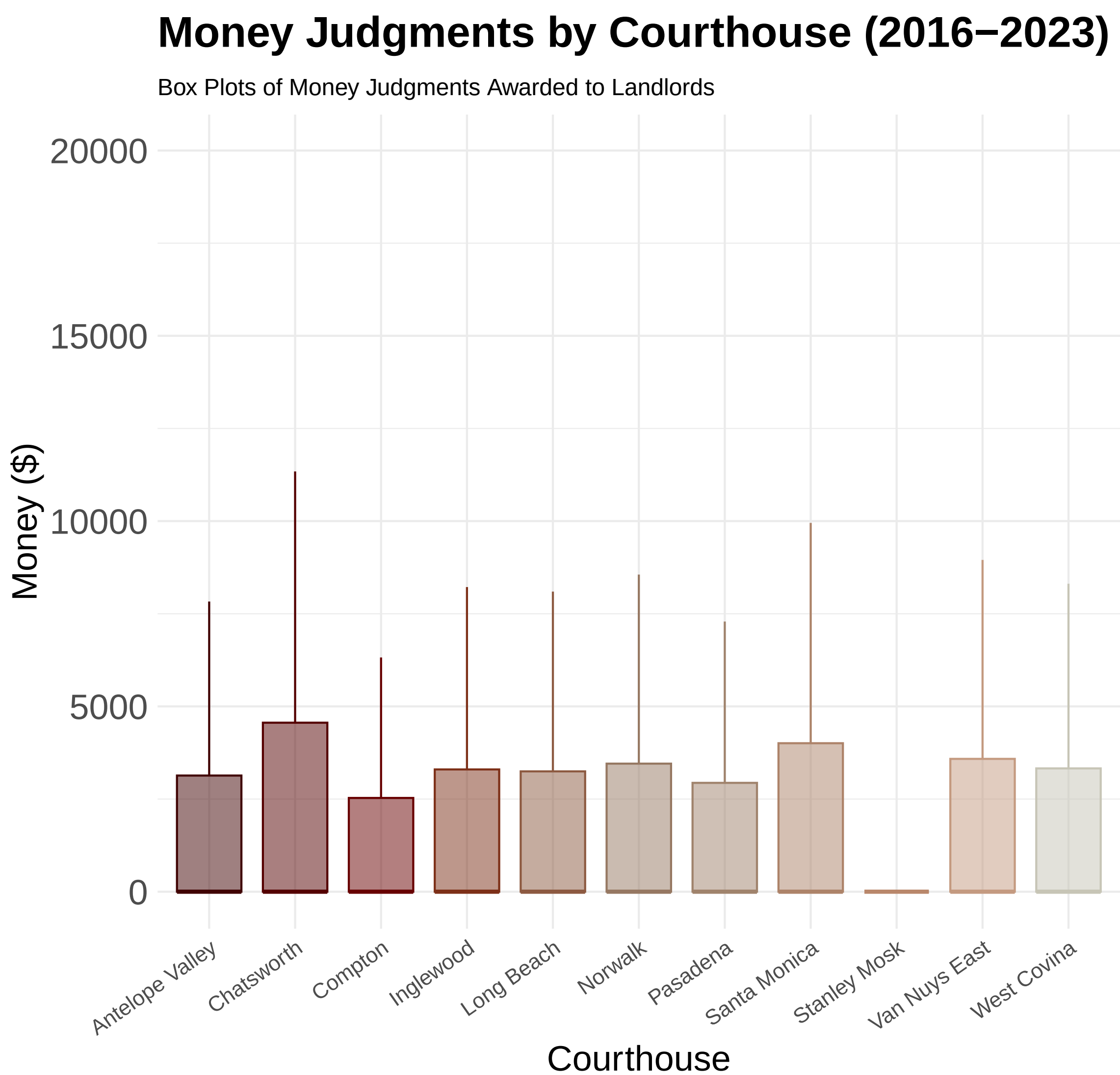
Appendix Figure D2

E Appendix E: Money Judgment Plots

Appendix E contains plots concerning money judgments in the observed eviction cases. We first plot the densities for money judgments across years (pooled courthouses) and box plots for courthouses (years pooled).



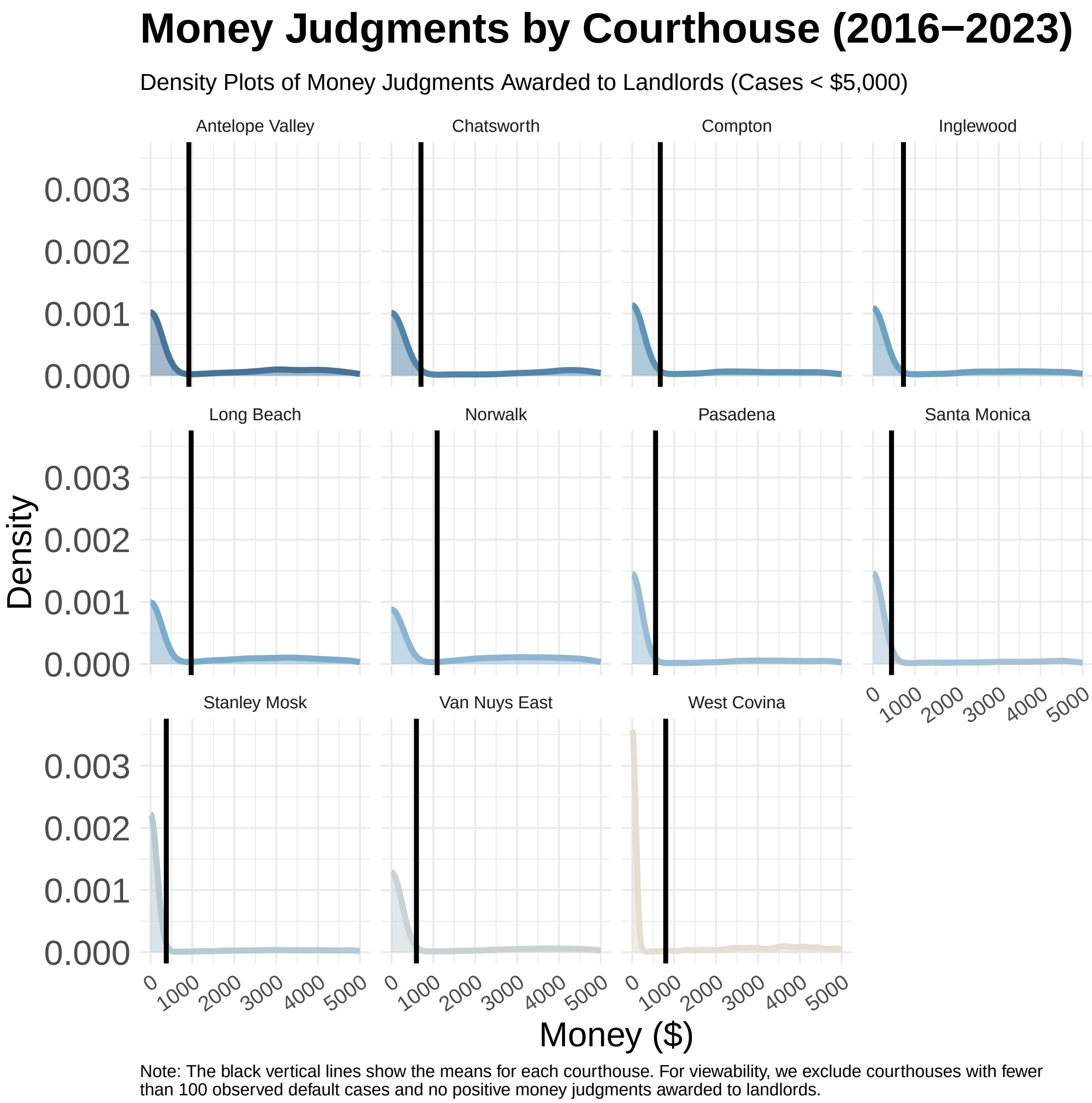
Appendix Figure E1



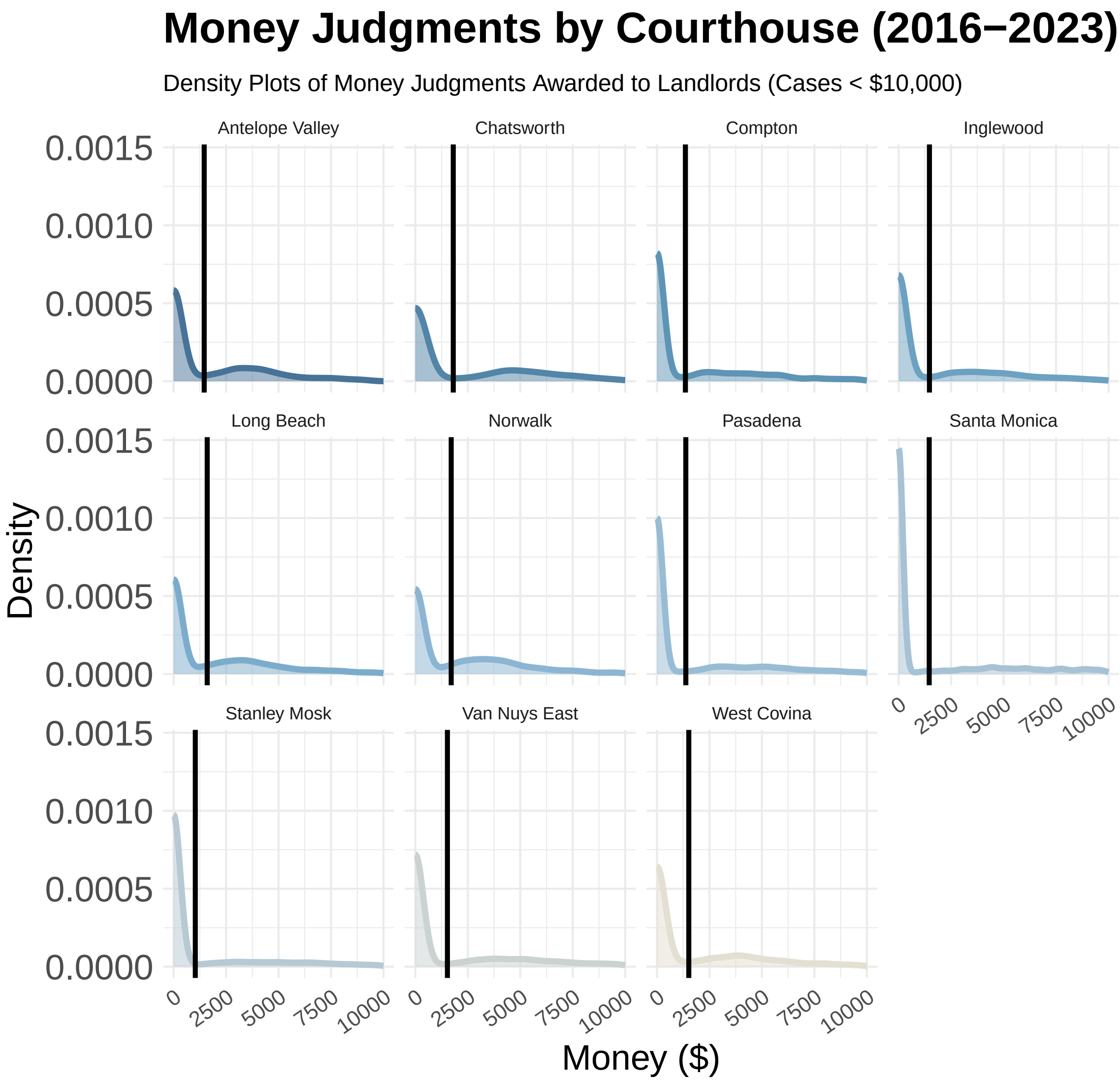
Note: For viewability, boxplots are restricted to the subset of cases with money judgments less than $20,000. We also exclude courthouses with fewer than 100 observed default cases and no positive money judgments awarded to landlords.

Appendix Figure E2

We also plot the densities for each courthouse across all years in the sample for different subsets: cases with total money judgments less than \$5,000, \$10,000, and \$20,000.

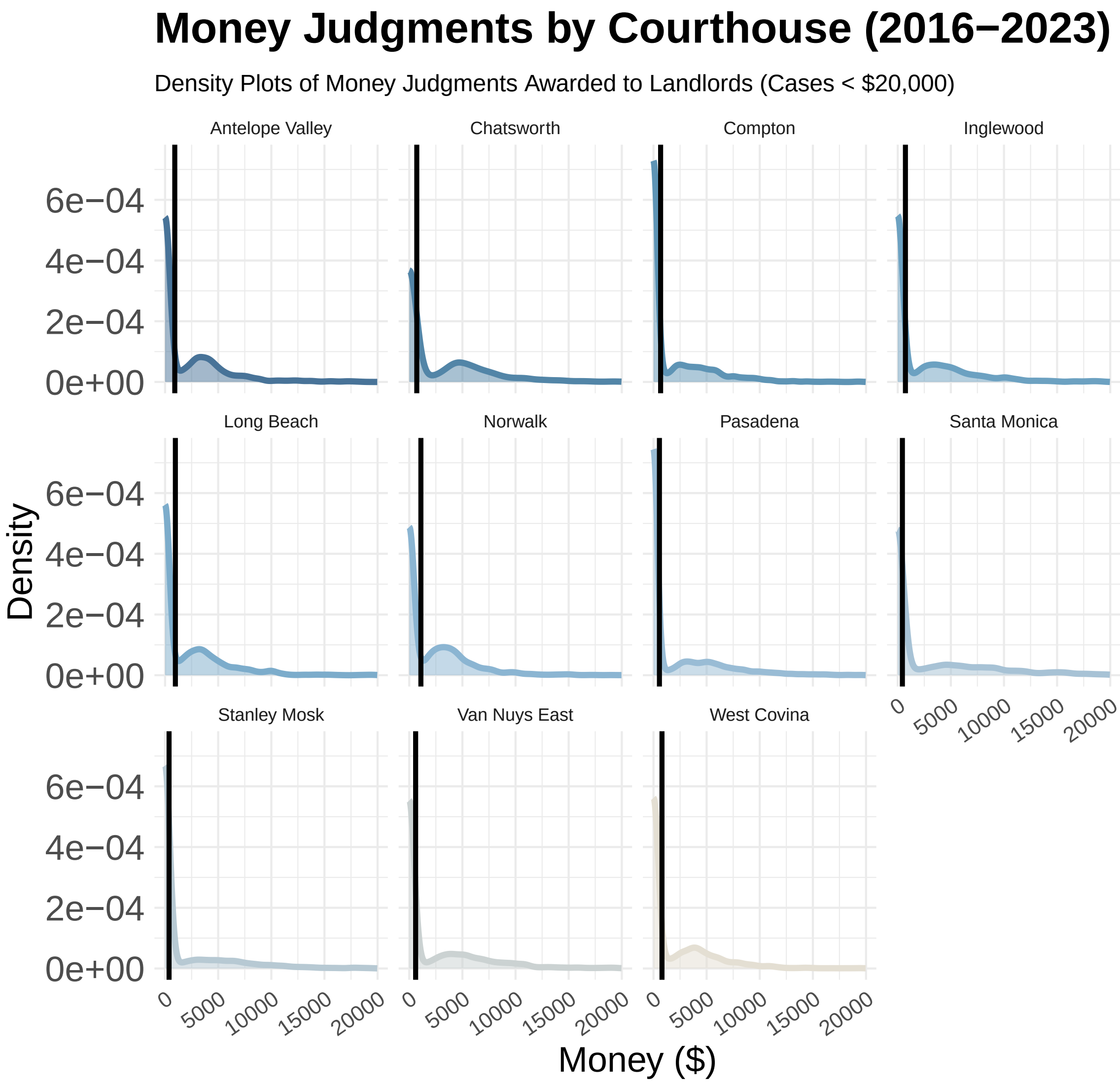


Appendix Figure E3



Note: The black vertical lines show the means for each courthouse. For viewability, we exclude courthouses with fewer than 100 observed default cases and no positive money judgments awarded to landlords.

Appendix Figure E4

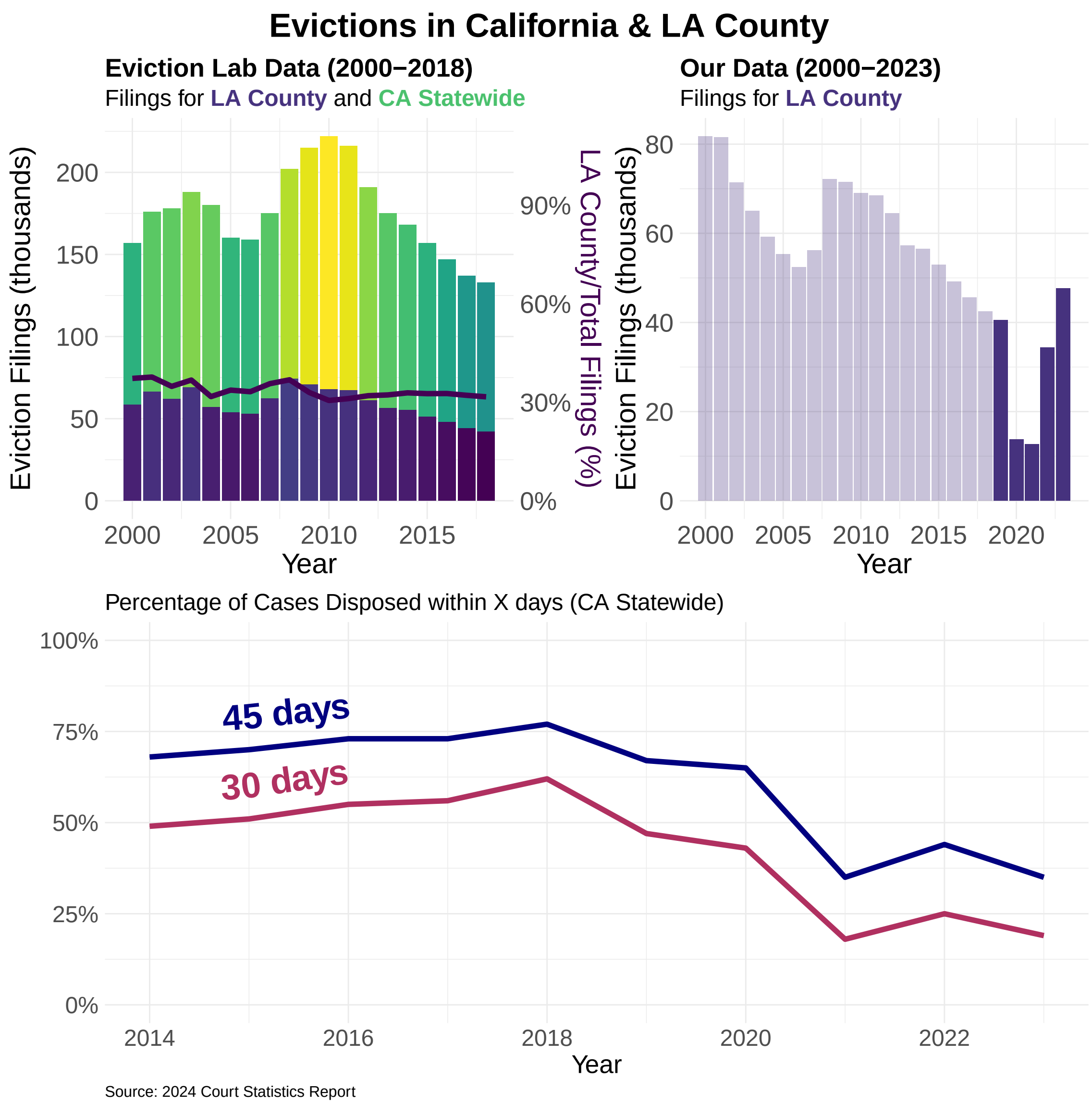


Note: The black vertical lines show the means for each courthouse. For viewability, we exclude courthouses with fewer than 100 observed default cases and no positive money judgments awarded to landlords.

Appendix Figure E5

F Appendix F: Data Overview

Appendix F gives an overview of the eviction data (from the Eviction Lab and data we collected) and CA statewide trends.



Appendix Figure F1. Eviction Filing Volume (CA & LA County) and Disposition Times (CA)

Note: The top left panel shows the modeled filing estimates from the Eviction Lab (Gromis et al., 2022). The top right panel shows the aggregate filing data we collected for LA County (2018-2023 emphasized). The bottom panel shows the statewide percentage of eviction cases disposed in 45 days (blue) and 30 days (red).

G Appendix G: Bandwidth Averaging

Appendix G further discusses our CLATE estimation procedure. We compare two estimators: the bandwidth averaging estimator and the non-parametric local linear estimator in the `np` package (Hayfield and Racine, 2008), which uses a cross-validation bandwidth selection procedure to fit the curve $\tau_C(z)$. By contrast, the bandwidth averaging estimator computes CLATE $\tau_C(z)$ for each z by computing the local linear estimator for many bandwidths h and then averaging across those bandwidths for each $z \in \text{supp}(Z)$.

We test these procedures in simulation below. To create the true CLATE curve $\tau_C(z)$, we generated simulated data with $10,000$ observations. We generate distance to assigned court ($Z \sim U[0, 50]$) and distance to the boundary ($X \sim U[-10, 10]$) uniformly. The treatment rule is $W_i = \mathbf{1}\{X_i \geq 0\}$, which is a sharp discontinuity design.

For an individual with a distance to the boundary x and distance to assigned court z, the expected outcomes (default rates) are given by $E_1(x, z)$ and $E_0(x, z)$, which are defined below by:

$$E_1(x, z) = \frac{1}{1 + \exp\left(-(0.5 - 0.1z + 0.3x)\right)}$$
$$E_0(x, z) = \frac{1}{1 + \exp\left(-(-0.5 - 0.1z + 0.3x)\right)}$$

For each individual, we then compute the potential outcomes $Y_i(1)$ and $Y_i(0)$ with noise:

$$Y_{1i} = E_1(X_i, Z_i) + \epsilon_i, \quad \epsilon_i \sim \mathcal{N}(0, 0.05) \tag{1}$$
$$Y_{0i} = E_0(X_i, Z_i) + \epsilon_i, \quad \epsilon_i \sim \mathcal{N}(0, 0.05) \tag{2}$$

The observed outcome follows the usual switching equation $Y_i = W_i Y_i(1) + (1 - W_i) Y_i(0)$.

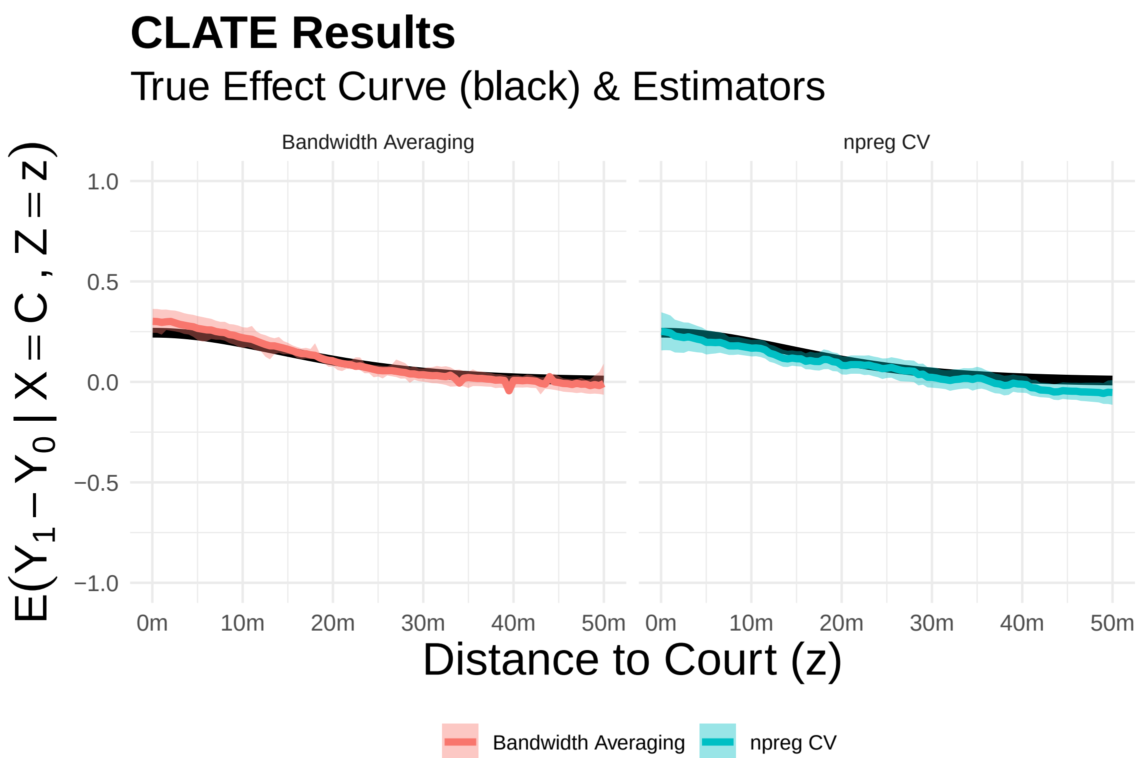
The conditional local average treatment effect curve is, for each (x, z), given by:

$$\text{CLATE}(x, z) = \mathbb{E}[Y_1 - Y_0 | X = x, Z = z] = E_1(x, z) - E_0(x, z). \tag{3}$$

Below, we plot in each panel the true treatment effect curve (black line) at the boundary $X = C$:

$$\text{CLATE}(C, z) = \underbrace{\mathbb{E}[Y_1 - Y_0 | X = C, Z = z]}_{:=\tau_C(z)}$$

where $C = 0$ here. We include the estimated curves—for the bandwidth averaging estimator (red) and the npreg cross-validated bandwidth estimator (blue)—in separate panels with pointwise confidence bands.



Appendix Figure G1. Simulation Example (Panels)
Note: The IMSE for the bandwidth averaging estimator (red) is 0.027. The IMSE for the npreg estimator (blue) using the cross-validation bandwidth selection procedure is 0.055.

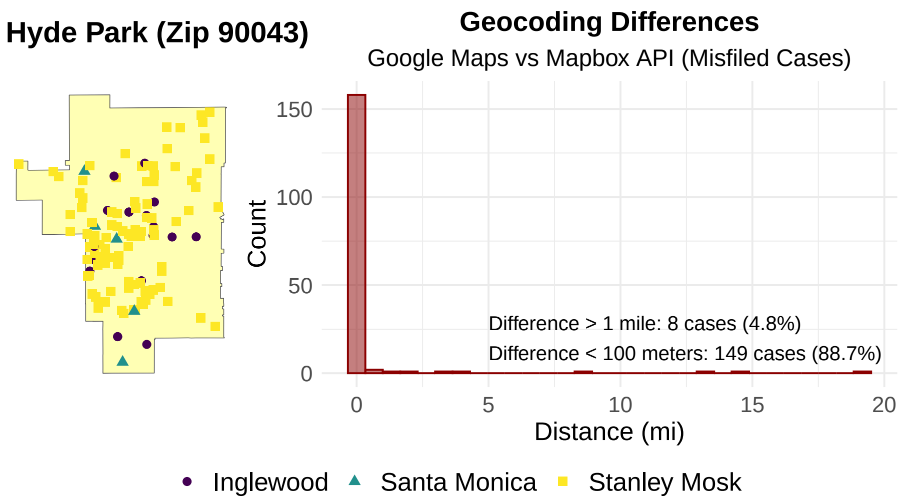
H Appendix H: Misfiled Cases

Appendix H continues the discussion of possible explanations for the observed phenomenon of misfiled cases. Specifically, we here explore three possibilities for misfiling. First, the courthouse assignment map could be wrong.[33] Second, cases might be incorrectly geo-located: the Mapbox API could be returning incorrect lat-long coordinates for certain addresses. Third, landlords may—knowingly or unknowingly—file cases in the incorrect courthouse, which is discussed above in Section 3.3.2.[34]

The first possibility is unlikely in regions with observed eviction cases. Although we cannot fully rule out that the map is incorrect in areas with no observed eviction cases, in regions with observed eviction records it is often not possible to draw a map that clearly separates the observed eviction cases into consistent, continguous filing regions. For example, in the left panel of Figure H1 there are eviction cases observed in Hyde Park (Zip 90043) from three different courthouses. There is no contiguous map separating Inglewood and Santa Monica misfiled cases from the correctly filed Stanley Mosk cases because misfiled cases are stacked "on top of" correctly filed cases.

[33] This could occur because neighborhoods and zip codes lack clear, defined geographical boundaries. Indeed, despite using the most current LA County geospatial data, there are some regions in the court filing table that do not correspond to the names given to particular areas of LA County by the assignment rule.

[34] A fourth possibility is that clerks or judges refiled the cases to change the venue. We found no instances of refiling among the cases we label misfiled.



Appendix Figure H1. Misfiling: Zip 90043 Example & Geolocating Check
Note: In the left panel, the background color is the most observed filing courthouse in the region. Each dot is a building with observed default eviction cases, which is colored and shaped by the observed courthouse in the eviction records. In the right panel, we manually checked 10% of the cases we label as misfiled with Google Maps. The histogram of the distances from the Google Maps and Mapbox API coordinates are shown above.

The second possibility is an error in geo-locating these cases. We manually checked a random subset of the misfiled cases for geo-location errors. We compared the lat-long Mapbox locations with the Google Maps lat-long locations. We assume for this exercise that the Google Maps coordinates are "ground truth," although in some cases there may be errors in Google Maps as well. In the right panel of Figure H1, we find that the vast majority (89%) of the geocoded coordinates from Mapbox are very close (< 100 meters) to the Google Maps coordinates. Only eight cases (4.8%) of the manual checks were clearly "wrong", meaning that the Google Maps coordinates were more than 1 mile from the location of the Mapbox API coordinates.

I Appendix I: Balance Tables at `rdrobust` bandwidths

We conduct balance tests using the `tableone` R package. The year built, total value, and taxable value covariates are building-level covariates (LA County Assessor). The imputed rent is the nearest geographic median rent (ACS). The means (and SDs), p-value, and standardized mean difference (SMD) for each covariate within the optimal bandwidth window for each courthouse pair are shown below. Some imbalance likely comes from the spatial nature of the data: comparing *all* buildings near boundary, which are not necessarily "directly" across each other at the boundary.

Appendix Table I1. Chatsworth and Van Nuys Balance Table: Means (SD)

	Chatsworth	Van Nuys East	p	SMD
Number Obs.	338	222		
Year Built	1927.66 (338.06)	1985.07 (136.33)	0.017	0.223
Total Value (millions $)	25.52 (36.33)	3.70 (8.19)	<0.001	0.829
Taxable Value (millions $)	25.30 (36.41)	1.87 (5.57)	<0.001	0.899
Imputed Rent	1253.42 (235.88)	1279.27 (294.78)	0.252	0.097

Appendix Table I2. Compton and Norwalk Balance Table: Means (SD)

	Compton	Norwalk	p	SMD
Number Obs.	157	107		
Year Built	1973.23 (26.76)	1920.10 (267.51)	0.014	0.279
Total Value (millions $)	2.08 (4.24)	4.88 (10.58)	0.003	0.347
Taxable Value (millions $)	2.08 (4.24)	4.88 (10.58)	0.003	0.347
Imputed Rent	1111.36 (224.62)	974.31 (181.11)	<0.001	0.672

Appendix Table I3. Compton and Stanley Mosk Balance Table: Means (SD)

	Compton	Stanley Mosk	p	SMD
Number Obs.	98	69		
Year Built	1948.51 (24.20)	1944.38 (19.94)	0.245	0.186
Total Value (millions $)	0.54 (0.75)	0.43 (0.40)	0.282	0.178
Taxable Value (millions $)	0.53 (0.75)	0.38 (0.43)	0.126	0.252
Imputed Rent	873.91 (110.89)	887.26 (48.06)	0.349	0.156

Appendix Table I4. Inglewood and Long Beach Balance Table: Means (SD)

	Inglewood	Long Beach	p	SMD
Number Obs.	31	33		
Year Built	1959.52 (15.09)	1962.55 (17.16)	0.457	0.187
Total Value (millions $)	0.71 (0.41)	0.51 (0.59)	0.119	0.398
Taxable Value (millions $)	0.71 (0.41)	0.51 (0.59)	0.120	0.397
Imputed Rent	1066.39 (111.35)	1168.55 (235.52)	0.032	0.555

Appendix Table I5. Pasadena and Stanley Mosk Balance Table: Means (SD)

	Pasadena	Stanley Mosk	p	SMD
Number Obs.	186	72		
Year Built	1970.89 (30.21)	1932.44 (233.15)	0.028	0.231
Total Value (millions $)	1.94 (4.15)	2.17 (3.32)	0.672	0.062
Taxable Value (millions $)	1.89 (4.13)	2.17 (3.32)	0.614	0.073
Imputed Rent	1383.95 (286.92)	1078.83 (198.18)	<0.001	1.237

Appendix Table I6. Pasadena and West Covina Balance Table: Means (SD)

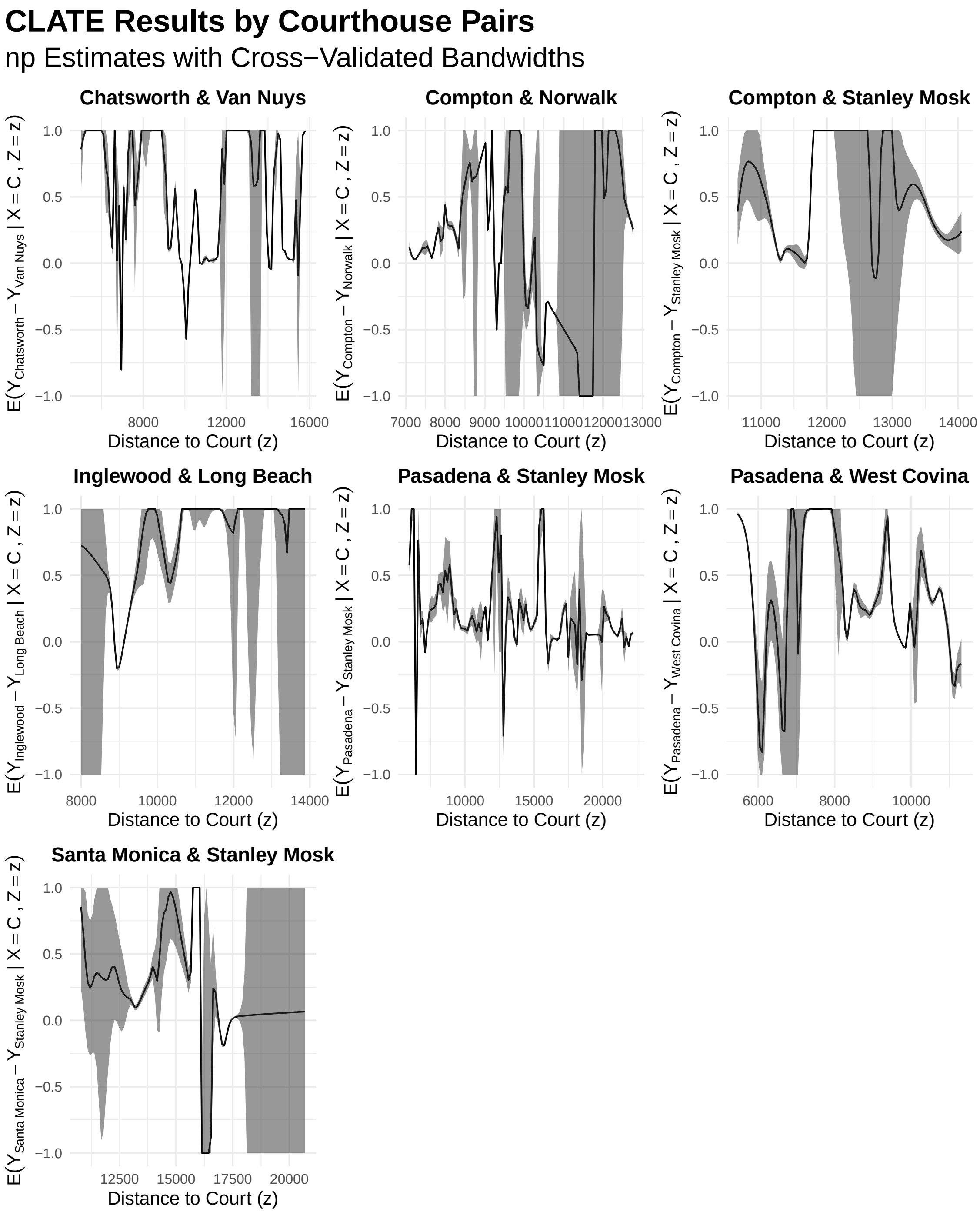
	Pasadena	West Covina	p	SMD
Number Obs.	54	106		
Year Built	1921.06 (267.00)	1962.12 (21.16)	0.116	0.217
Total Value (millions $)	0.94 (1.68)	4.24 (10.22)	0.020	0.450
Taxable Value (millions $)	0.94 (1.68)	4.00 (10.02)	0.027	0.426
Imputed Rent	1095.93 (206.56)	1076.47 (100.40)	0.423	0.120

Appendix Table I7. Santa Monica and Stanley Mosk Balance Table: Means (SD)

	Santa Monica	Stanley Mosk	p	SMD
Number Obs.	374	316		
Year Built	1953.63 (105.11)	1939.99 (192.04)	0.238	0.088
Total Value (millions $)	5.42 (14.17)	6.81 (14.80)	0.209	0.096
Taxable Value (millions $)	5.38 (14.17)	6.81 (14.80)	0.197	0.098
Imputed Rent	1197.96 (276.53)	1243.93 (270.81)	0.028	0.168

J Appendix J: np CLATE Estimates

Appendix J gives the np package CLATE estimates.



Appendix Figure J1. np Package CLATE Estimates with CV Bandwidths