

Eviction Reduction Policies

Do More Courts Reduce Defaults in LA County?*

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Abstract

Eviction is a leading cause of housing instability and eviction reduction is a policy priority. Yet many strategies to reduce evictions lack empirical footing and the effectiveness of any particular policy is likely to hinge on the mechanisms determining eviction outcomes. Empirical work quantifying how and how much different policies causally effect eviction outcomes is therefore needed. Using data on LA County eviction filings, this paper empirically examines how court-based procedural policies impact eviction. By exploiting an August 2017 change in court policy, this paper quantifies the extent to which changing the number of eviction courts causally effects default evictions via changes in tenant costs. The paper shows that the August 2017 reform to the number of courts had insignificant effects on eviction outcomes. The findings highlight the need for both short-term and long-term strategies to address the eviction and affordable housing crises.

Keywords: eviction, housing, court rules, empirical legal studies

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1 Introduction

The lack of affordable housing is a growing crisis across the United States. By some estimates, “tens of millions of families, across red and blue states, struggle with rent and home prices.”¹ By another metric, more than half of renting households are cost-burdened: they spend more than 30% of their income on housing costs.² According to polling,³ 69% of U.S. adults are now “very concerned” about rising housing costs.⁴ Consequently, housing policy is an increasingly pressing priority for elected officials.⁵

One key consequence of the housing crisis is a growing number of evictions. Because a growing portion of household income is spent on rent, evictions are rising.⁶ The repercussions for evicted tenants are significant: reduced credit access; reduced earnings; increased hospital visits; lower educational performance; and increased housing instability, including homelessness.⁷ Because eviction is linked to these varied and pernicious social ills,⁸ understanding the causes and consequences of eviction is an important goal for researchers. Yet many factors impact eviction outcomes, so understanding which policies deliver temporary versus lasting relief to renters is empirically challenging. Consequently, appropriately tailoring eviction and housing policy is an important but practically difficult endeavor.

¹Conor Dougherty, *America’s Affordable Housing Crisis*, N.Y. TIMES (Mar. 27, 2024).

²See U.S. Dep’t of Hous. & Urban Dev., *HUD ACS Cost Burden Measure* (July 2024).

³Pew Research Ctr., *Economic Ratings and Concerns* (Sept. 2024).

⁴The impact is felt unevenly across demographic groups: for instance, younger renters (18-29) are particularly likely (55%) to say “the availability of affordable housing is a major problem in their local community.” See Pew Research Ctr., *A Growing Share of Americans Say Affordable Housing Is a Major Problem Where They Live* (Jan. 2022).

⁵In California, for example, Governor Newsom has signed into law numerous housing reforms aimed at reducing rent and increasing housing supply. See Office of Governor Gavin Newsom, *Governor Newsom Signs Bipartisan Housing Package and Launches Prop 1 Homekey+ Initiative* (Sept. 19, 2024); see also Office of Mayor Karen Bass, *Mayor Karen Bass Declares a State of Emergency on Homelessness* (Dec. 12, 2022).

⁶The most common reason for eviction is non-payment of rent. See, e.g., Matthew Desmond, *Evicted* (2017); Los Angeles City Controller’s Office, *Eviction Notices* (2025).

⁷Robert Collinson, John Eric Humphries, Nicholas Mader, Davin Reed, Daniel Tannenbaum and Winnie van Dijk, *Eviction and Poverty in American Cities*, 139 QUARTERLY J. ECONOMICS 57 (2024); Matthew Desmond, *Eviction and the Reproduction of Urban Poverty*, 118 AM. J. SOC. 88 (2012); Bruce D. Meyer, Angela Wyse, and Ilina Logani, *Life and Death at the Margins of Society: The Mortality of the U.S. Homeless Population*, THE REVIEW OF ECONOMICS AND STATISTICS (2025).

⁸See, e.g., Matthew Desmond, *Evicted* (2017); Matthew Desmond and Rachel Tolbert Kimbro, *Eviction’s Fallout: Housing, Hardship, and Health*, 94 SOCIAL FORCES 295 (2015); Robert Collinson, John Eric Humphries, Nicholas Mader, Davin Reed, Daniel Tannenbaum and Winnie van Dijk, *Eviction and Poverty in American Cities*, 139 QUARTERLY J. ECONOMICS 57 (2024); Michael C. Lens, Kyle Nelson, and Ashely Gromis, *The Neighborhood Context of Eviction in Southern California*, 19 CITY AND COMMUNITY 912 (2020).

The focus in this paper is assessing available interventions for effectiveness at decreasing evictions, particularly *default* evictions. Default evictions occur when tenants don't show up to housing court and landlords win *by default*. Default is not easily reversed and accelerates the process of lock out. Although some level of default is inevitable in any court system, eliminating unnecessary or unfair defaults is a key part of the access-to-justice literature.⁹

Optimally tailoring the default rate matters for efficiency and social welfare reasons. Zero default may strain court resources with little upside if benefits accrue only to tenants with a persistent inability-to-pay.¹⁰ On the other hand, landlords assured default wins may hastily (or improperly) evict tenants with legal or practical grounds for staying in the rental unit.¹¹ In partial equilibrium, policy changes which impact the default probability may affect the total number of evictions in unexpected ways.¹² And, in equilibrium, eviction protections tend to increase rents for all tenants, thereby complicating welfare analysis.¹³

These issues therefore necessitate empirical analysis to understand how tenants, landlords, and courts respond to changes in the eviction policy apparatus. This paper begins by mapping the empirical terrain, reviewing legal and economic studies on the effectiveness of various interventions at reducing eviction and defaults in theory and in practice. I suggest that there are three emerging intervention approaches with at least some empirical support: (1) representation-based approaches focused on providing tenants with legal resources at or before eviction court, (2) tenant cost approaches focused on reducing the cost of using or getting to court, and (3) market-based approaches aimed at increasing housing supply and reducing rents.

This paper next offers an empirical study of how part of the eviction machine—a procedural policy expanding the number of eviction courts—impacts default evic-

⁹See, e.g., D. James Greiner and Andrea Matthews, *The Problem of Default, Part I* (2015).

¹⁰See Boaz Abramson, *The Equilibrium Effects of Eviction Policies* (2021) (unpublished manuscript) for discussion of equilibrium eviction policy.

¹¹If landlords face a legal rule which assures them of a tenant default, they may evict paying tenants for discriminatory or otherwise illegal reasons. See *infra* (discussing composition effects from procedural reforms). Similarly, landlords may be too quick to evict if tenants experience only temporary income shocks. In this case, society may have practical reasons to give tenants who are likely-to-repay a chance to do so before starting the eviction process. (Eviction protections with this purpose—e.g. mandatory mediation—functionally grant tenants an extended eviction notice period.)

¹²See *infra* Section 2.

¹³See, e.g., Boaz Abramson, *The Equilibrium Effects of Eviction Policies* (2021) (unpublished manuscript). The impact on all tenants is largely due to an *ex ante* screening problem: landlords don't know with certainty what "type" of tenant you are, so they increase rents to account for the possibility (and added cost) of evicting types that are unable-to-pay rent.

tions via the tenant cost channel. Using causal inference tools, I quantify how this procedural reform causally effect eviction outcomes (e.g. default counts) over time. Using variation across time, I estimate how the policy effects eviction outcomes in LA County, which is one of the more problematic eviction systems in the U.S.¹⁴

Specifically, the empirical study focuses on a court assignment policy shock in Los Angeles County in August 2017.¹⁵ I estimate how expanding the number of eviction courts from 8 to 11 impacted defaults. The court expansion changed the distance-to-court for some (but not all) tenants, resulting in some tenants facing increased costs (longer distance-to-court), some facing decreased costs (shorter distance-to-court), and some unaffected (no change in distance-to-court). Comparing these cohorts, I find mixed results from the court expansion procedural reform. Defaults increase for those with the increased costs, but there is considerable uncertainty stemming from a small treatment cohort. Additional robustness checks in the appendices suggest that either results are insignificant or do not align with expectations: namely,

The legal takeaway is that default judgments are persistent and resistant to legal reforms. Additional legal resources (more courts, more judges, more lawyers) or procedural reforms are not guaranteed to meaningfully halt broader legal and socioeconomic trends, at least in the case of eviction default and relatively limited legal reforms. This is part of an emerging set of findings that procedural legal interventions that increase legal resources, reduce tenant costs, or otherwise alter the form of the proceeding may have only limited observed effects in the aggregate.¹⁶

This paper is also part of a series of works to determine the relative effectiveness of procedural versus structural housing reforms in combating eviction.¹⁷ The

¹⁴See Susan Lanzas, *Stay Housed Los Angeles: Safeguarding Tenants' Rights Beyond Rent Control*, 41 ARIZ. J. INT'L & COMP. L. 489, 490 (2025) ("Los Angeles, the nation's second-largest city, consistently ranks amongst the least affordable housing markets and has one of the highest eviction rates.")

¹⁵A companion piece uses a regression discontinuity design to compare regions near the boundary of two eviction courthouse districts. The intuition is that nearby renters are "similar" along observable and unobservable dimensions, so this comparison approximates an experiment. There, we estimate the causal effect of court assignment is between 0.7–23.1 percentage points for seven different courthouse pairs. See Matthew Estes & Kyle Nelson, *Justice Divided, Justice Denied? The Effects of Court Rules on Eviction Outcomes in Los Angeles County* (2025) (unpublished manuscript).

¹⁶See *infra* Section 2.

¹⁷Because tenants often face a large resource disadvantage in eviction cases, procedural reforms aim to "level the playing field" for tenants in cases against better-resourced landlords. By contrast, because non-payment of rent is the primary reason for eviction, structural reforms tend to focus on reducing rent and housing prices by increasing the housing supply. See [Appendix A](#) for further discussion; see also Benjamin F. Teresa, Kathryn L. Howell, I-Shian Suen, Amanda Robinson, and Roy Sabo, *Moving From Crisis to Stability? The Success and Limits of an Eviction Prevention Program*, 35 HOUSING POLICY DEBATE 452 (2025) (describing upstream and downstream eviction

overarching research goal is understanding how these levers—court-based procedural policies and market-based structural reforms—can reduce evictions and housing instability for vulnerable populations. This paper contributes to the procedural half of the broader scholarly agenda to understand how to reduce evictions. But eviction scholars may need to reorient focus away from procedures and toward rental markets. On this view, legal procedure functions less as a long-term remedy and more as a short-term patch on the flat tire of a fundamental problem in housing supply.

The remainder of the paper is structured as follows. [Section 2](#) reviews the empirical and theoretical findings from the law, economics, sociology, and urban planning literatures, focusing mostly on empirical studies of methods to reduce evictions generally and default evictions specifically. [Section 3](#) reviews the eviction process and court assignment in LA County, describing the legal court assignment mechanism which forms the basis of the empirical exercise. Next, in [Section 4](#), I describe the collected data qualitatively and quantitatively. [Section 5](#) is the heart of the paper: I empirically test whether changes in court assignment policy reduced default evictions. Finally, I discuss implications for how these policies may or may not reduce evictions in [Section 6](#).

2 Eviction Reduction Strategies

This section briefly reviews the main findings from a diverse, interdisciplinary eviction literature. I begin with the access-to-justice problem posed by default eviction judgments and possible solutions suggested by the literature. I then turn to detailing the emerging economic picture of the costs and benefits of procedural reforms: although strengthening eviction protections for tenants may give them time and/or improve case outcomes, the economic costs of eviction protections in equilibrium are less discussed. Finally, I note the extensive descriptive literature on eviction correlates, which sheds light on how eviction disproportionately affects vulnerable communities.

2.1 The Problem of Default & Possible Solutions

From an access-to-justice perspective, default judgments are a continuing problem across the law. Default judgments occur when plaintiffs obtain judgments against defendants because defendants do not contest the case. Because unrepresented defendants often default at higher rates, “such behavior presents an access to justice prevention policies).

problem in that low- and middle-income people are benefiting from—and are in fact disproportionately suffering adverse consequences from—the formal administration of justice.”¹⁸ Defaults are often considered, then, to be a legal harm in themselves:

“From a systemic point of view, court actors and judges consider high default rates a public harm. The administration of justice suffers when parties do not meet in an adversarial proceeding in order to resolve claims.”¹⁹

Understanding the legal and non-legal factors that determine default is important to craft policy solutions. Although other procedural interventions—including mediation and/or technology policy—may merit further empirical study,²⁰ I focus here on three legal factors inspired by the literature that partially explain the eviction and default phenomena: (1) lack of resources (esp. legal representation), (2) tenant costs of getting to court, and (3) market structure (esp. rental prices).

2.1.1 Representation-Based Interventions (*Civil Gideon*)

Likely the most common policy suggestion to assist tenants in eviction court is to provide some form of legal representation. Because tenants are often unrepresented and eviction is a summary proceeding, some scholars believe evictions are “patently unfair”²¹ or even “violent.”²² Empirical scholars, accordingly, have studied whether some forms of legal representation can remedy the disparities between landlord and tenant in eviction proceedings.

Empirical studies have used a variety of methods from different legal settings

¹⁸D. James Greiner and Andrea Matthews, *The Problem of Default, Part I* (2015).

¹⁹D. James Greiner and Andrea Matthews, *The Problem of Default, Part I* (2015). (string-cite to court cases therein disfavoring default judgments too).

²⁰For example, it is possible that mediation would “help parties reach better outcomes in eviction cases,” at least for smaller, non-corporate landlords. See Brian Bieretz, Kimberly Burrowes, and Emily Bramhall, *Getting Landlords and Tenants to Talk*, URBAN INSTITUTE (2020); cf. Cassie Chambers Armstrong and Christopher J. Ryan Jr., *Rural Renting: An Empirical Portrait of Eviction*, 93 U. Cin. L. Rev. 1, 36 (2024). Another possibility is that technology—and artificial intelligence (AI) in particular—will level the informational playing field in eviction and reduce defaults. *But see* Drew Simshaw, *Access to AI Justice: Avoiding an Inequitable Two-Tiered System of Legal Services*, 24 YALE J. L. & TECH. 150 (2022) (for AI skepticism). The effectiveness of such possibilities may turn on what mechanisms most impact default and eviction outcomes.

²¹Andrew Scherer, *The Case Against Summary Eviction Proceedings: Process as Racism and Oppression*, 53 SETON HALL L. REV. 1 (2022).

²²Andrew Scherer, *Stop the Violence: A Taxonomy of Measures to Abolish Evictions*, 51 FORDHAM URB. L.J. 1329 (2023).

across the U.S. For example, Greiner et. al. (2012, 2013)²³ study the effects of legal representation interventions on eviction outcomes in a randomized controlled trial (RCT). These studies find mixed results. In one study, the authors find:

“no statistically significant evidence that [the offer] of a traditional attorney-client relationship, as compared to a referral to the [lawyer for the day] program, had a large (or any) effect on the likelihood that the occupant would retain possession; on the financial consequences of the dispute; on the judicial involvement in or attention to the litigation cases; or on any other outcome.”²⁴

In the other study, the authors find that full legal representation following an initial intake and screening process mattered: 34% of treated occupants (who received full legal representation from a legal services staff attorney) versus 62% of control occupants (who received an instructional clinic only) lost possession of their units.²⁵ Observational studies on the effectiveness of NYC’s access-to-counsel program are similar, finding that tenants are less likely to face adverse eviction judgments, especially those at the highest risk of possessory judgment.²⁶

Still, there are limits to the effectiveness of legal representation. For example, some eviction defenses may be unlikely to benefit tenants in practice.²⁷ And the direct costs can be large: in 2024, NYC spent around \$179.5 million on tenant legal services, including the Universal Access to Counsel (UAC) program.²⁸

²³D. James Greiner, Cassandra Wolos Pattanayak, and Jonathan Hennessy, *The Limits of Unbundled Legal Assistance: A Randomized Study in a Massachusetts District Court and Prospects for the Future*, 126 HARV. L. REV. 901 (2013); D. James Greiner, Cassandra Wolos Pattanayak, and Jonathan Philip Hennessy, *How Effective Are Limited Legal Assistance Programs? A Randomized Experiment in a Massachusetts Housing Court* (2012).

²⁴D. James Greiner, Cassandra Wolos Pattanayak, and Jonathan Philip Hennessy, *How Effective Are Limited Legal Assistance Programs? A Randomized Experiment in a Massachusetts Housing Court* (2012) at 5-6.

²⁵D. James Greiner, Cassandra Wolos Pattanayak, and Jonathan Hennessy, *The Limits of Unbundled Legal Assistance: A Randomized Study in a Massachusetts District Court and Prospects for the Future*, 126 HARV. L. REV. 901, 927 (2013); see also *id.* at 936-937. The results suggest there are limits to “unbundled” legal assistance in the form of instructional clinics.

²⁶See Mike Cassidy and Janet Currie, *The Effects of Legal Representation on Tenant Outcomes in Housing Court: Evidence from New York City’s Universal Access Program*, 222 J. PUBLIC ECONOMICS 104844, Table 3 (2023) (using OLS and IV to estimate the impact of access-to-counsel program on variety of eviction outcomes).

²⁷See, e.g., Nicole Summers, *The Limits of Good Law: A Study of Housing Court Outcomes*, 87 U. CHICAGO L. REV. 145, Table 3 (2020) (finding that most represented tenants with likely meritorious warrants of habitability defenses do not win rent abatement).

²⁸See https://www.nyc.gov/assets/hra/downloads/pdf/services/civiljustice/OCJ_Annual_Report_2024.pdf.

2.1.2 Tenant Costs & Spatial Considerations

Another factor from the literature that may cause defaults are spatial costs.²⁹ As Prescott (2017) puts it, the idea is that:

“[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.”³⁰

Put differently, the idea is that factors which increase the costs or effort—longer commutes, for instance—for litigants getting to court tend to increase defaults.

Other studies confirm that the cost of getting to court is important in eviction cases. In Philadelphia, Hoffman and Strezhnev³¹ find that a one hour increase in travel time increases the probability of eviction default by 3.9 to 8.6 percentage points, arguing that distance-to-court causes default evictions. The authors find that this “transit effect” disappeared when courts made virtual accommodations in eviction proceedings during the COVID-19 pandemic.

In LA County, the specter of getting to court looms large in eviction proceedings, especially for vulnerable renter populations. As argued by tenants-plaintiffs in *Miles v. Wesley*:³²

[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 court-rooms 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.

Shortly after *Miles*, the LA Superior Court system expanded the number of regional courthouses that process eviction cases, but many of the distance concerns cited in

²⁹See, e.g., Matthew Clair, Jesus Orozco, and Iris H. Zhang, *Spatial Burdens of State Institutions: The Case of Criminal Courthouses*, 99 SOCIAL SERVICE REV. (2025) (arguing that spatial features affect court accessibility).

³⁰J.J. Prescott, *Improving Access to Justice in State Courts with Platform Technology*, 70 VANDERBILT L. REV. 1993, 1995 (2017).

³¹David A. Hoffman & Anton Strezhnev, *Longer Trips to Court Case Evictions*, 120 PROC. NAT'L ACAD. SCI. (2023).

³²801 F.3d 1060 (9th Cir. 2015).

Miles continue to exist. As elaborated below, this paper studies how the number of courts affects default outcomes, by using data before and after a court expansion policy shock. Because the policy shock changed the tenant distance-to-court distribution for some but not all tenants, I study whether increased (resp. decreased) tenant costs increase (resp. decrease) default outcomes.

2.1.3 Market Structure, Housing Supply, and Reducing Rents

A final factor that is important but relatively neglected by eviction scholars is the structure of housing markets themselves. Although less discussed by eviction scholars, supply-and-demand arguments suggest that supply-side housing reforms should reduce the number of evictions *ceteris paribus* because they reduce rents.³³ Indeed, as shown in Mast (2023)³⁴, new market-rate construction of even more expensive rental housing improves affordability in the market for low-income housing. The mechanism—called a “migration chain”³⁵—is simply (albeit provocatively) illustrated by the following graphic:

³³See generally Nathaniel Baum-Snow & Gilles Duranton, *Housing Supply and Housing Affordability* (NBER Working Paper) (discussing extensive literature on housing supply and prices).

³⁴Evan Mast, *JUE Insight: The Effect of New Market-Rate Housing Construction on the Low-Income Housing Market*, 133 J. URBAN ECONOMICS 103383 (2023); see also Cristina Bratu, Oskari Harjunen, and Tuukka Saarimaa, *JUE Insight: City-wide Effects of New Housing Supply: Evidence from Moving Chains*, 133 J. URBAN ECONOMICS 103528 (2023) (showing “empirical evidence on how the moving chain mechanism unfolds in a European city”).

³⁵Evan Mast, *JUE Insight: The Effect of New Market-Rate Housing Construction on the Low-Income Housing Market*, 133 J. URBAN ECONOMICS 103383 (2023).



Figure 1. Migration Chains in Housing

Note: The figure is from a post on X by Michael Wiebe (dated July 28, 2025).

The intuition is that constructing new housing, even at the high-end of the market, may have spillover effects: “geographically localized shocks are likely to have ripple effects on other parts of the region.”³⁶ Consequently, failure to construct new housing can impact renters at the lower end of the income distribution disproportionately, with rents increasing the most in the lowest-income zip codes.³⁷

Although there are laws and regulations at all governing levels that affect the supply of housing, one set of rules of growing interest for reform are zoning and land use regulations.³⁸ Such reforms could reduce evictions: because the proximate cause of an eviction filing is most often non-payment of rent, interventions which reduce rental prices should (on average) reduce the number of evictions holding constant

³⁶Evan Mast, *JUE Insight: The Effect of New Market-Rate Housing Construction on the Low-Income Housing Market*, 133 J. URBAN ECONOMICS 103383 (2023).

³⁷Pew Research Ctr., *New Housing Slows Rent Growth Most for Older, More Affordable Units* (Jul. 31, 2025); *see also id.* at Figure 2 (“Rents in Older, Less Expensive Apartments Decreased Most in High-Supply Metropolitan Areas”). The Pew researchers’ explanation for the finding sounds in migration chain reasoning: “When not enough homes are built in high-income neighborhoods, people who would have lived in those neighborhoods can usually afford to move into middle-income neighborhoods, and middle-income residents can usually afford to move into low-income neighborhoods, but residents of low-income neighborhoods have nowhere to turn.” *Id.*

³⁸See, e.g., Ezra Klein & Derek Thompson, *Abundance* (2025); *but see* Christopher S. Elmendorf, Clayton Nall, and Stan Oklobdzija, *Do Housing Supply Skeptics Learn? Evidence from Economics and Advocacy Treatments* (2024) (noting that support for zoning liberalization is “much less stable than support for housing price controls and demand subsidies”).

the renter population.³⁹ Eviction scholars to-date have not empirically tested these possibilities because:

“[A]lthough researchers have established the centrality of zoning policies to a wide array of social problems and conditions, they lack access to national longitudinal zoning and land use data, which would help researchers identify the causal effects of exclusionary zoning.”⁴⁰

As new data becomes available, researchers will be able to test how housing and eviction outcomes respond to changes in zoning and land use regulations.⁴¹

2.2 The Costs and Benefits of Reform: Equilibrium Rents & Composition Effects

Although well-intended, the welfare effects of access-to-justice interventions can depend on the policy method chosen. In general, legal assistance will “delay or prevent eviction,”⁴² which are the primary gains accruing to tenants facing eviction.⁴³ Yet, legal assistance programs generate direct and indirect costs. On the direct side, some interventions may have high direct costs (e.g. right-to-counsel reforms) because they involve costly lawyering. And, on the indirect side, legal assistance to renters tends to raise rents in equilibrium: because landlords face a screening problem when deciding to whom they rent, reducing their ability to quickly re-rent in non-payment situations will tend to increase market rents.⁴⁴ Empirically, prior work on right-to-counsel finds

³⁹In general equilibrium, the effect could go either way because lower rents tend to induce immigration. See, e.g., Minjee Kim & Hyojung Lee, *Upzoning and Gentrification: Heterogeneous Impacts of Neighborhood-Level Upzoning in New York City*, 62 URBAN STUDIES 2009 (2025).

⁴⁰Matthew Mleczko & Matthew Desmond, *Using Natural Language Processing to Construct a National Zoning and Land Use Database*, 60 URBAN STUDIES 2564 (2023).

⁴¹See, e.g., Vincent Rollet, *Can We Rebuild a City? The Dynamics of Urban Redevelopment*, Working Paper (2025) (studying urban redevelopment in response to zoning reforms); Susan Lanzas, *Stay Housed Los Angeles: Safeguarding Tenants’ Rights beyond Rent Control*, 41 ARIZ. J. INT’L & COMP. L. 489, 497-499 (2024) (discussing rent control).

⁴²Rob Collinson, John Eric Humphries, Stephanie Kestelman, Scott Nelson, Winnie van Dijk, and Daniel Waldinger, *Equilibrium Effects of Eviction Protections: The Case of Legal Assistance*, Working Paper(2024)

⁴³Accord Abraham Bell and Gideon Parchomovsky, *A Theory of Property*, 90 CORNELL L. REV. 531, 614 (2005) (“[I]t is clear that there is considerable value in stable ownership for both tenant and landlord, in particular, because tenants will often develop sentimental value for their leased premises, while landlords will frequently be better suited to extract value (due to specialized knowledge) from their premises than anyone else in the market.”).

⁴⁴Landlords could also respond by increasing screening efforts or reducing maintenance costs, but Collison et al (2024) find little evidence for this.

that the “cost to tenants due to higher rent prices more than offsets the benefits from better eviction court outcomes.”⁴⁵

Other studies find that procedural changes may backfire rather than improve access-to-justice in different ways. Consider, for example, Niblett and Yoon (2017),⁴⁶ which studies outcomes from a Canadian policy shock which made increased the recoverable amount in small claims cases. The change was meaningful because the informal small claims court was less expensive than Ontario Superior Court. The authors found that plaintiff suits did not increase significantly, but there were *compositional* effects. Specifically, they found that lower dollar claims (those less than the previous cap \$10,000) decreased following the jurisdictional change.⁴⁷ The authors conclude that access-to-justice efforts can have unintended regressive effects⁴⁸ and note that the optimal structure of access-to-justice interventions may depend on the court design perspective.⁴⁹

To fully understand the welfare effects of eviction reduction policies, a necessary ingredient is credible evidence for how tenants, landlords, and markets react. As noted by Collinson et. al. 2024, quasi-experimental evidence of legal assistance interventions is difficult because “it is often not clear how to choose a reasonable comparison group.”⁵⁰ One possible strategy, the authors note, is leveraging a difference-in-differences design for nearby zip codes treated at different times.⁵¹ This paper similarly uses a difference-in-differences strategy by exploiting quasi-experimental variation stemming from changes in distance-to-court due to a court policy shock.

2.3 The Correlates of Eviction

Finally, this paper also contributes to the correlational research on factors affecting eviction outcomes (including default), such as individual tenant and landlords characteristics. Studies in this vein look at many characteristics correlated with evic-

⁴⁵Collinson et al (2024) at 4.

⁴⁶Anthony Niblett & Albert H. Yoon, *Unintended Consequences: The Regressive Effects of Increased Access to Courts*, 14 J. Empirical Legal Stud. 5 (2017).

⁴⁷See *id.* at Figure 2.

⁴⁸The authors further find: “Evidence suggesting that congestion in the courts may be driving these regressive effects is mixed.”

⁴⁹Niblett & Yoon (2017) (“While economists and legal scholars have looked at the optimal structure of courts from the perspective of appeals, error correction, and *ex ante* rule setting, few have looked at the question of the optimal structure of courts from the perspective of *ex post* dispute resolution for the purposes of access to justice.”).

⁵⁰Collinson et. al. (2024) at 2.

⁵¹Collinson et. al. (2024) at 2-3.

tion, including: demographic and income correlates of eviction,⁵² including race⁵³ and gender⁵⁴; neighborhood and spatial correlates with eviction;⁵⁵ and other case characteristics related to eviction and default,⁵⁶ including urban-rural considerations.⁵⁷ Below, I detail descriptive findings, including whether observable demographic factors appear balanced across LA County courthouses. I find that key racial, gender, income, and representation variables appear mostly balanced across assigned eviction courthouse.

3 Eviction Process & Institutional Background

This section gives a brief overview of the typical eviction case in LA County. First, I describe the standard timeline for eviction cases, as summarized in Estes & Nelson (2025).⁵⁸ Next, I explain how eviction cases are assigned to courthouses and how the number of eviction courts evolved over time. It is the change in eviction court assignment policy over time which is the key quasi-experimental variation I utilize for causal inference.

3.1 Eviction Process

The eviction process begins when a landlord serves an eviction notice on a tenant, most of which are for non-payment of rent.⁵⁹ Eviction notices give tenants a few days to “cure” their lease breach by paying unpaid rent to the landlord,⁶⁰ although

⁵²See generally Matthew Desmond, *Evicted* (2017); Matthew Desmond, *Eviction and the Reproduction of Urban Poverty*, 118 AM. J. SOC. 88 (2012); Matthew Desmond and Rachel Tolbert Kimbro, *Eviction’s Fallout: Housing, Hardship, and Health*, 94 SOCIAL FORCES 295 (2015).

⁵³See, e.g., Nicole Summers and Justin Steil, *Pathways to Eviction*, 50 LAW & SOCIAL INQUIRY 129 (2025) (“Race has repeatedly been shown to be the strongest predictor of facing eviction and is more predictive than income level or any other sociodemographic characteristic.”)

⁵⁴Sarah Buhler and Isabelle MacLean, *Gendered eviction in Saskatchewan*, 50 QUEEN’S L.J. 1 (2024).

⁵⁵See Michael C. Lens, Kyle Nelson, and Ashely Gromis, *The Neighborhood Context of Eviction in Southern California*, 19 CITY AND COMMUNITY 912 (2020).

⁵⁶See, e.g., Erik Larson, *Case Characteristics and Defendant Tenant Default in a Housing Court*, J. EMPIRICAL LEGAL STUDIES (2006).

⁵⁷Cassie Chambers Armstrong and Christopher J. Ryan Jr., *Rural Renting: An Empirical Portrait of Eviction*, 93 U. CIN. L. REV. 1 (2024).

⁵⁸Matthew Estes & Kyle Nelson, *Justice Divided, Justice Denied? The Effects of Court Rules on Eviction Outcomes in Los Angeles County* (2025) (unpublished manuscript).

⁵⁹Matthew Estes & Kyle Nelson, *Justice Divided, Justice Denied? The Effects of Court Rules on Eviction Outcomes in Los Angeles County* (2025) (unpublished manuscript) (in LA City, over 96% of the notices in 2023 were for non-payment of rent).

⁶⁰The amount of unpaid rent and number of eviction notices vary at the zip-code and building levels. See Kyle Nelson, Ashley Gromis, Yiwen Kuai, and Michael C. Lens, *Spatial Concentration and*

some landlords may permit informal arrangements for repaying rental arrears (such as negotiated payment plans outside of formal court proceedings). If the tenant does not cure non-payment, the landlord may then initiate an eviction by filing an eviction (unlawful detainer) lawsuit.⁶¹

After being notified of an eviction proceeding initiated against them,⁶² tenants must file an Answer⁶³ with the court.⁶⁴ If tenants do not appear to 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 past due rent if they win at trial.

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 some number of days to move out.⁶⁵ 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 2](#).

Spillover: Eviction Dynamics in Neighborhoods of Los Angeles, California, 2005-2015, 31 HOUSING POLICY DEBATE 670 (2021) (for discussion of the spatial autocorrelation in eviction variables).

⁶¹In the LA Superior Court system the filing costs \$240-\$385. See Los Angeles Superior Court, *Civil Fee Schedule* (2024) (nos. 11 and 14).

⁶²Tenants are considered notified after being served the Summons and Complaint forms.

⁶³In LA County, tenants pre-2025 had 5 days to file the Answer. 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.

⁶⁴The 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>. Filing fees vary over time, but in LA County the 2024 fee in eviction actions where the contested amount of rent is less than \$12,500 is \$225. See Los Angeles Superior Court, *Civil Fee Schedule* (2024) (no. 15). But note that there are fee waiver applications available.

⁶⁵In LA County, tenants formally have five days to move out after receipt of the Notice to Vacate.

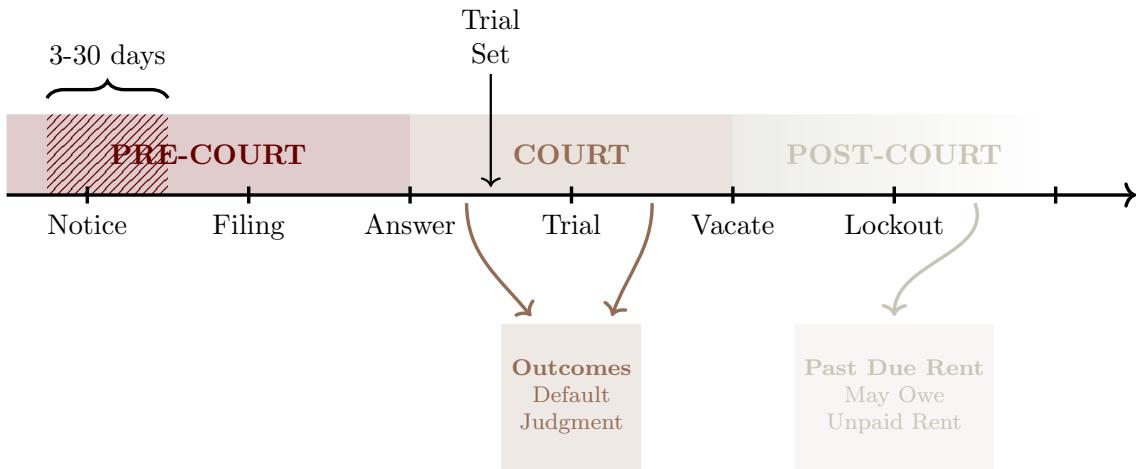


Figure 2. Eviction Timeline

Note: This figure is reproduced from Estes & Nelson (2025).

This eviction timeline here may does not reflect the exact process for every eviction case, but it gives a rough picture of the steps and time pressures tenants face once an eviction notice has been served.⁶⁶ With the timeline of typical events specified, I now turn to explaining the court assignment procedure.

3.2 LA County Eviction Courts: Assignment and Expansion

According to LA County court rules,⁶⁷ eviction cases are assigned to courthouses based on a unique spatial mechanism. Under the rules, eviction cases:

“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 [Eviction] cases.”

Since August 2017, 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.⁶⁸

⁶⁶The eviction timeline outlined above omits, for instance, any special motions that may arise. Eviction moratoria and other COVID-19 protections also altered the 2020–2022 process, e.g., giving tenants more time or limiting the landlord’s ability to force the tenant to vacate.

⁶⁷LASC Local Rule 2.3(a)(2)

⁶⁸*But see infra* (discussing different courthouse assignment rule from 2015–August 2017).

Table 1. Zip Code Table for Eviction 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 shown in the left panel of Figure 3. The court districts differ in the land area they cover, but all courts—except for the Stanley Mosk courthouse in downtown Los Angeles—hear roughly the same number of cases each year. This map has been in effect since 2017, but prior to 2017 the number of courthouse districts fluctuated due to local budget constraints.⁶⁹ This is shown in the right panel of Figure 3.

⁶⁹In particular, the 2008 financial crisis resulted in a dramatic reduction in the number of eviction courts. 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). See Matthew Estes & Kyle Nelson, *Justice Divided, Justice Denied? The Effects of Court Rules on Eviction Outcomes in Los Angeles County* (2025) (unpublished manuscript); Kyle Nelson, *The Political Determinants of Access to Justice*, Working Paper (2023).

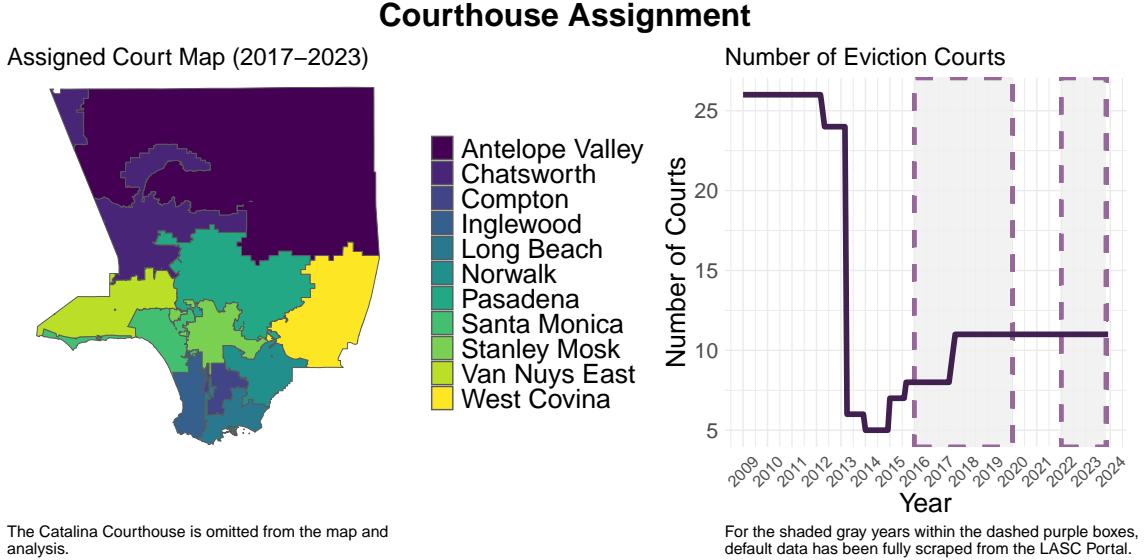


Figure 3. LA County Eviction Court Assignment

Note: The assignment map (Late 2017–2025) is shown in the left panel. The number of courthouse districts expanded in late 2017, which is shown in the right panel. *See also* Estes & Nelson (2025) for further discussion.

In the causal analysis of Section 5, I leverage the expansion of the number of courthouses in August 2017. Because the addition of new courthouses changed the distance-to-court for many tenants, I use quasi-experimental variation from the 2017 change in court procedure to isolate the causal effect of increasing or decreasing the distance-to-court. In related work,⁷⁰ I utilize the other source of variation from the court assignment policy: the spatial nature of the assignment mechanism (as shown in the left panel of Figure 3).

4 Data Collection & Descriptive Evidence

This section briefly describes the data collection process, including information collected from primary sources (docket records), linked datasets (e.g. assessor data, Census variables), and imputation methods (e.g. racial characteristics). Next, I describe the general characteristics of the data, including looking at rough demographic balance across courthouses. Finally, this section estimates the relationship between distance-to-court and eviction outcomes (notice counts, default probability, default counts).

⁷⁰Matthew Estes & Kyle Nelson, *Justice Divided, Justice Denied? The Effects of Court Rules on Eviction Outcomes in Los Angeles County* (2025) (unpublished manuscript).

4.1 LA Default Eviction Records Data

The data I use here includes tens of thousands of individual docket records in eviction cases scraped from the LA Superior Courts from 2016-2025.⁷¹ The docket records contained both structured and unstructured information, including the following fields at the top of the record:

Case Number: [10 character case number]
Filing Courthouse: [court]
Filing Date: [date]
Case Type: [Unlawful Detainer Residential]
Status: [Default]
Plaintiff: [landlord name]
Defendant: [tenant name]
Attorney for Plaintiff: [attorney name]
Attorney for Defendant: [attorney name]

From the individual-level text files, I used regular expressions (regex) to extract this information for each individual record, along with the following variables from the unstructured “register” of case actions: address information, monetary awards, judge, and other 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.⁷²

Using the individual-level case address information, I geocode the address to get location information for each docket record⁷³ which allows encoding⁷⁴ how many

⁷¹Unless otherwise noted, 2020-2022 is excluded from all analysis and discussion because of local, state, and national eviction moratoria. Data from 2024 is also unavailable, but the records include data from the first months of 2025 (Jan–May 2025).

⁷²See Matthew Estes & Kyle Nelson, *Justice Divided, Justice Denied? The Effects of Court Rules on Eviction Outcomes in Los Angeles County* (2025) (unpublished manuscript) (describing further details).

⁷³This can also be linked to LA County Assessor data. The Assessor data includes building-level covariates, including, e.g., the age of the building.

⁷⁴See Matthew Estes & Kyle Nelson, *Justice Divided, Justice Denied? The Effects of Court Rules on Eviction Outcomes in Los Angeles County* (2025) (unpublished manuscript) for more details on

default evictions are observed at each address i at time t :

$$\text{default}_{it} = \text{number of default evictions at address } i \text{ in month } t$$

In what follows, I generally focus only on buildings that have at least one observed default eviction (or an observed eviction notice) unless otherwise noted.⁷⁵

4.2 Mapping the Data & Descriptive Findings

Using the records data, I then link each case to further information. Estes & Nelson (2025)⁷⁶ linked data to building assessment data from the LA County Assessor. Here, I supplement the data further in two ways. First, I included several Census variables at the census block group level, including: median gross rent (in dollars) for renter-occupied housing units, median household income (in dollars), and demographic variables (e.g. gender,⁷⁷ race, total census block group population).⁷⁸ Second, I used Bayesian imputation software from the R package `wru`⁷⁹ and tenant names to impute race for each observed default eviction. The software works to “predict individual race/ethnicity using surname, first name, middle name, geolocation, and other attributes” by “utiliz[ing] Bayes’ Rule (with optional measurement error correction) to compute the posterior probability of each racial category for any given individual.”⁸⁰

Figure 4 below details the final dataset in spatial and descriptive terms. In the top left panel of Figure 4, I plot the geocoded defaults across LA County (2016–2025). The map underneath the defaulting address points is the 2017–2025 court assignment map, with eviction court district shaded in the same colors as the observed defaults

data collection and linking, including information on the case availability, FOIA data on the total number of evictions in a courthouse each month, geocoding information, and linking to LA County assessment data.

⁷⁵Assessed properties for which there are no observed evictions, observed defaults, or eviction notices may differ from properties with evictions in important but unobservable respects.

⁷⁶Matthew Estes & Kyle Nelson, *Justice Divided, Justice Denied? The Effects of Court Rules on Eviction Outcomes in Los Angeles County* (2025) (unpublished manuscript).

⁷⁷The gender variable “Female” in the bottom table of Figure 4 is the average number of female residents in the census block group.

⁷⁸See also Mike Cassidy and Janet Currie, *The Effects of Legal Representation on Tenant Outcomes in Housing Court: Evidence from New York City’s Universal Access Program*, 222 J. PUBLIC ECONOMICS 104844, Table 2 (2023) (for Census variables included in their study).

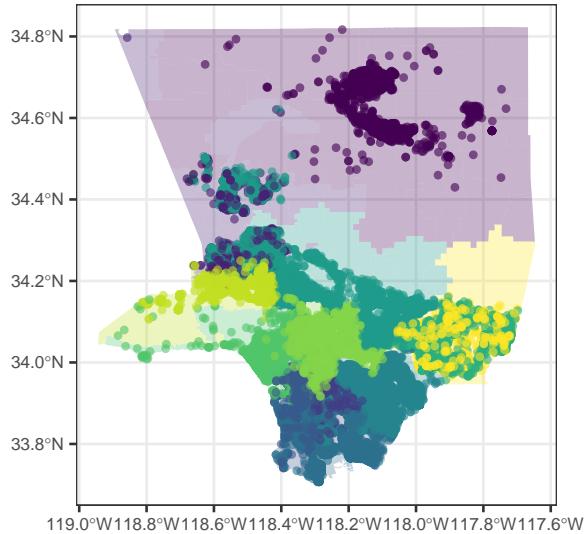
⁷⁹Kabir Khanna, Brandon Bertelsen, Santiago Olivella, Alexander Rossell Hayes, and Kosuke Imai, *wru: Who are You? Bayesian Prediction of Racial Category Using Surname, First Name, Middle Name, and Geolocation*, R Package (2024).

⁸⁰*Id.*

but transparently. The top right table of [Figure 4](#) shows the average distance-to-court (in miles) for cases by observed filing courthouse under two court assignment policies. For example, for cases actually filed in Compton courthouse pre-August 2017, the average distance-to-court was 8.88 miles; by contrast, the average distance-to-court post-August 2017 would be 3.44 miles. Whether the change in the distance-to-court distribution induced by the August 2017 court expansion policy meaningfully impacted default evictions is studied below.⁸¹ Note that in some cases, the decrease in average distance-to-court was large whereas in other cases it is modest (or, in the Stanley Mosk case, a slight increase in the average distance-to-court).

⁸¹See *infra* Section 5

Default Evictions by Filing Court



Average Distance-to-Court (miles)

Court	Pre Aug 2017	Post Aug 2017
Antelope Valley	5.29	5.20
Chatsworth	23.11	7.85
Compton	8.88	3.44
Inglewood	9.69	4.61
Long Beach	4.66	3.73
Norwalk	5.71	5.05
Pasadena	10.75	8.59
Pomona	8.34	6.19
Santa Monica	6.64	4.66
Stanley Mosk	3.71	3.76
Van Nuys East	6.71	5.66
West Covina	8.11	6.20

Summary Statistics by Court

Court	White Prob.	Black Prob.	Hispanic Prob.	Female	Income	Rent	% Represented
Antelope Valley	0.31	0.16	0.43	1036.12	50842.38	1256.90	1.59
Chatsworth	0.28	0.10	0.51	935.23	83057.96	1908.95	1.01
Compton	0.20	0.13	0.57	971.15	52876.50	1324.40	0.87
Inglewood	0.30	0.16	0.41	935.28	68685.96	1592.32	0.44
Long Beach	0.26	0.13	0.49	895.27	58458.76	1415.00	0.88
Norwalk	0.14	0.06	0.72	953.78	62371.87	1439.52	1.63
Pasadena	0.26	0.09	0.48	922.87	72317.52	1766.50	1.93
Pomona	0.16	0.06	0.65	967.41	67706.66	1588.46	1.67
Santa Monica	0.35	0.15	0.35	856.46	80247.71	1927.76	2.83
Stanley Mosk	0.26	0.13	0.44	813.54	54047.10	1515.82	1.17
Van Nuys East	0.27	0.10	0.50	994.93	68398.69	1816.32	1.46
West Covina	0.16	0.06	0.62	988.69	66997.75	1623.61	0.80

Figure 4. Observed Defaults & Descriptive Findings

Note: The top-left map shows where default evictions occur geographically in LA County (2016–2025) as colored points, with the Late 2017–2025 court assignment map plotted beneath it. The top-right table shows the average distance-to-court by observed filing courthouse under the 2016–Aug 2017 and Aug 2017–2025 courthouse assignment policies. The bottom table shows summary averages by observed filing court for all available default records using: imputed race data (first three columns), geo-linked Census data (next three columns), and representation data from the docket records (last column).

Finally, the bottom table of [Figure 4](#) shows averages in several covariates by courthouse. For example, the average imputed white probability (following the imputation procedure described briefly above) is 31.25 for observed eviction cases filed in Antelope Valley courthouse. Average incomes across the filing courthouses range from \$50,842–\$83,058 approximately. Average rents are positively correlated with the median income and range from \$1257–\$1928. The percentage of observed cases with tenant legal representation is below 3% across filing courts. The observed data is consistent with the standard empirical portrait of eviction: tenants are most often minority renters with below median incomes who lack legal representation⁸² at eviction proceedings.

4.3 Additional Evidence: Default and Distance-to-Court Relationship

Using the data, I also estimate the relationship between distance-to-court and default outcomes using binned averages and non-parametric regressions. First, I use data on all rental units from the LA County Assessor dataset⁸³ to encode whether each unit at rental addresses has an observed default in a given year.⁸⁴ In [Figure C1](#), I use this data to estimate the default probability as a function of distance-to-court pooling across years. The average default probabilities are shown in 5-mile distance-to-court intervals. Next, using non-parametric local linear regressions, I also plot estimated curves in [Figure C2](#). In the left panel of [Figure C2](#), the estimated relationship shows that the default probability is low but roughly increasing as distance-to-court increases (at least up to a certain distance). Finally, I estimate the relationship between the number of observed defaults and distance-to-court for addresses observed in the court docket records only. This exercise gets at the spatial concentration of defaults across LA County and is shown in the right panel of [Figure C2](#): the number of observed default evictions is a complicated non-linear function of distance-to-court.⁸⁵

⁸²This is especially unsurprising here because our data is largely restricted to default evictions. See also Matthew Estes & Kyle Nelson, *Justice Divided, Justice Denied? The Effects of Court Rules on Eviction Outcomes in Los Angeles County* (2025) (unpublished manuscript). Still, some tenants in default do have attorneys recorded in the docket data.

⁸³See also Matthew Estes & Kyle Nelson, *Justice Divided, Justice Denied? The Effects of Court Rules on Eviction Outcomes in Los Angeles County* (2025) (unpublished manuscript).

⁸⁴For example, if unit A at address i in year t has a default but units B and C do not, then unit A is encoded as a 1 whereas B and C are encoded as zeroes.

⁸⁵The number of defaults is highest at the smallest distances, largely due to a high number of evictions in downtown LA relatively close to the Stanley Mosk courthouse. The estimated curve then decreases between 0–5 miles, before increasing from around 5–13 miles, at which point it decreases and levels off at 1 default. This is because most addresses at the highest distance-to-court values have only a few observed defaults.

Because there are some disadvantages to using either the Assessor data or court record counts only, I also repeat the reduced-form estimation in [Appendix C](#) using newly available on the near universe of eviction notices in LA City. Using a new legal reporting requirement of eviction notices to the LA City Controller's Office,⁸⁶ I am able to define the population of at-risk tenant addresses as those appearing in the City Controller eviction notice data. See [Appendix C](#) (and [Figure C4](#), in particular) for further details.

5 Court Expansion Study

This section uses the LA County eviction data and changes in court assignment policy over time. Specifically, I estimate the impact of expanding the number of eviction courts in August 2017. Because this expansion changed the distance-to-court for some but not all locations, I model the default probability as a function of the change in distance-to-court. I show that units with an increased distance-to-court following the court expansion policy had higher average defaults post-August 2017 relative to control units (no change in distance-to-court) and units with a decreased distance-to-court.

Next, I describe a framework—the difference-in-differences (DID) design—to assess causality. The framework is popular in empirical legal studies and the intuition underlying it is explained visually. Using this framework, I find that DID estimates imply directional treatment effects consistent with the distance-as-tenant-cost model, but only for units with large changes in distance-to-court. The effect is subject to uncertainty and the interpretation is constrained by limited sample size.

5.1 Expanding the Number of Eviction Courthouses & Key Expectations

Over time, LA County has expanded the number of eviction courthouses.⁸⁷ In 2015, seven eviction courthouses—plotted in the left-most map of [Figure 5](#)—heard eviction cases in LA County.⁸⁸ But in September 2015, the LA County Superior Court system

⁸⁶Failure to report the eviction notice to the City Controller constitutes an affirmative defense to the eviction.

⁸⁷See *supra* [Figure 3](#) (right panel).

⁸⁸Note that for 2015 and 2016, due to eviction data unavailability we cannot know with certainty the contours of the eviction map in the northern-most parts of LA County or in some of the south-eastern regions. Only zip codes with uniquely-assigned courts and no potentially mis-filed cases under the then-operating eviction assignment rule are shown in the left and middle maps. *See also* Matthew Estes & Kyle Nelson, *Justice Divided, Justice Denied? The Effects of Court Rules on*

increased the number of eviction courts from seven to eight, splitting off part of the Pasadena eviction court district for coverage by the Pomona courthouse. This is shown in the middle map of [Figure 5](#). Then, in August 2017, LA County expanded the number of courthouses more substantially, adding 3 new courthouses and sending Pomona court cases to the West Covina courthouse.

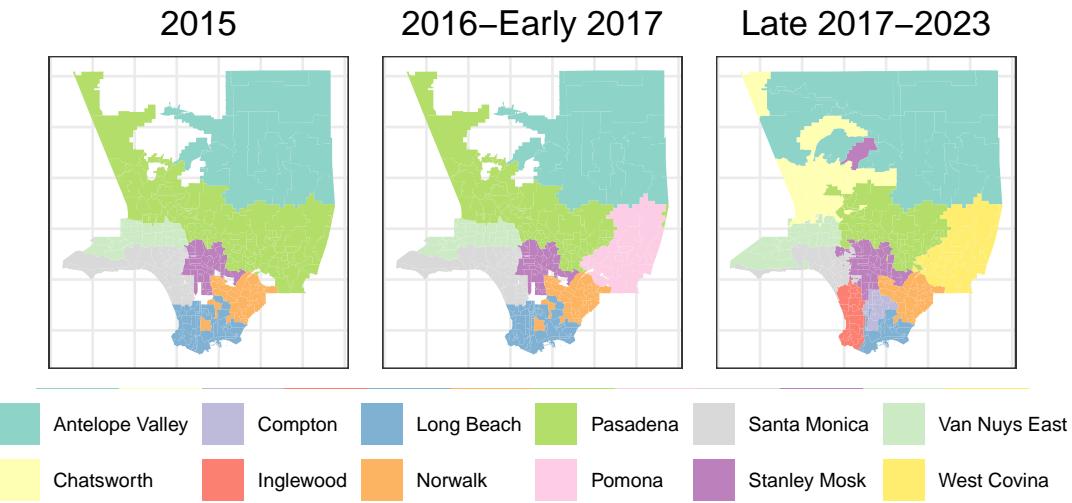


Figure 5. LA County Courthouse Expansion

Note: All maps omit the Catalina courthouse, where there are few eviction cases and no observed defaults.

In this section, I utilize data collected from 2016 onwards to study the effect of the August 2017 policy change in court assignment on tenants. Because the court assignment policy change induced changes in distance-to-court, I test whether default evictions responded to changes consistent with the tenant cost theory of defaults. Recall that on this theory, defaults are caused by the myriad costs of getting to court, with distance-to-court being a large obstacle in LA County specifically.⁸⁹ We therefore expect that tenants with increased costs—such as higher difficulty in physically getting to court—should experience higher rates of default. Conversely, lowering costs by assigning tenants to closer courthouses should tend to decrease defaults.⁹⁰

Accordingly, I begin by splitting tenants into three cohorts.⁹⁰ The first group I call the Increase-Treated group: tenants in this group experienced an increase in

Eviction Outcomes in Los Angeles County (2025) (unpublished manuscript) (discussing misfiling, map creation, and the assignment rule).

⁸⁹ See *supra* (discussing *Miles v. Wesley*).

⁹⁰ To formalize the cohorts, define the following variable:

$$\Delta_i = D_{i,\text{Post-Expansion}} - D_{i,\text{Pre-Expansion}}$$

distance-to-court because of the August 2017 court expansion policy shock, which represents an increase in the tenant cost of getting to court. The second group is the Decrease-Treated group faced decreased “costs” post-August 2017, meaning they experienced a decrease in distance-to-court following the court expansion. Finally, the last group is the Control group, which did not undergo a change in court assignment and therefore experienced the same distance-to-court before and after August 2017.

The changes from the August 2017 policy shock on distance-to-court are summarized in [Figure 6](#). In the left panel of [Figure 6](#), I show the histogram of the changed distances across all of LA County. The large black bar (apprx. 23,000 addresses) are Controls: they did not experience any change in distance-to-court from the August 2017 court expansion. The dark blue bars plotted to the left (less than zero) are Decrease-Treated units: tenants living at these addresses were closer to court because of the August 2017 court expansion. Although fewer in number than the Control group, the Decrease-Treated cohort outnumbers the Increase-Treated cohort: units with an increased distance-to-court following the August 2017 court expansion are shown in dark red bars on the histogram.

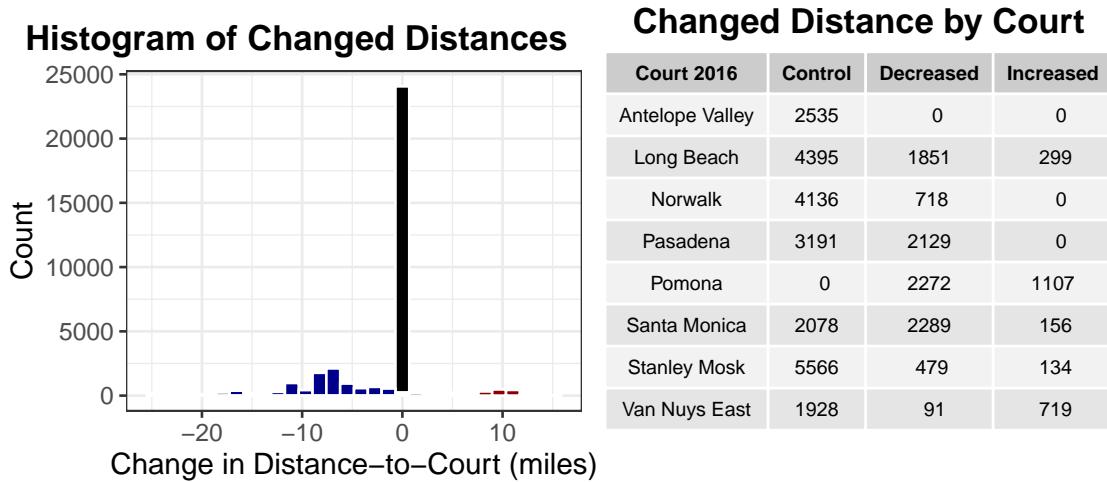


Figure 6. Changes in Distance-to-Court from 2017 Court Expansion Policy

Note: The left panel shows a histogram of changes in distance-to-court following the August 2017 Court Expansion: controls are shown in black, decrease-treated units in blue, and increase-treated units in red. The right panel table shows the cohort counts by 2016 assigned courts.

The number of addresses within each cohort are broken up by assigned 2016 court

where $D_{i,Post-Expansion}$ (resp. $D_{i,Pre-Expansion}$) is the distance from unit i to the assigned courthouse after (resp. before) the courthouse expansion policy in August 2017. The cohorts are defined as: Increase-Treated ($\Delta_i > 0$), Decrease-Treated ($\Delta_i < 0$), and Control ($\Delta_i = 0$).

in the right panel of [Figure 6](#). Four of the 2016 court districts had some units in all three cohorts (Long Beach, Santa Monica, Stanley Mosk, Van Nuys East), two were only in the Control or Decrease-Treated cohorts (Norwalk & Pasadena), one had no Control units (Pomona), and one had only Control units (Antelope Valley).

Using these cohorts, I next turn to estimating the average number of default evictions over time for each cohort. In [Figure 7](#), I plot estimates of the average number of defaults for the cohorts in different colors for each year with collected and available data.⁹¹ The average number of default evictions for the Increase-Treated cohort is shown in red, the average for the Decrease-Treated cohort is shown in blue, and the average for Controls is shown in black. The court expansion policy shock is shown as the vertical dashed line in August 2017.

Average Defaults by Cohort Increased, Control, and Decreased – Piecewise Constant Fits

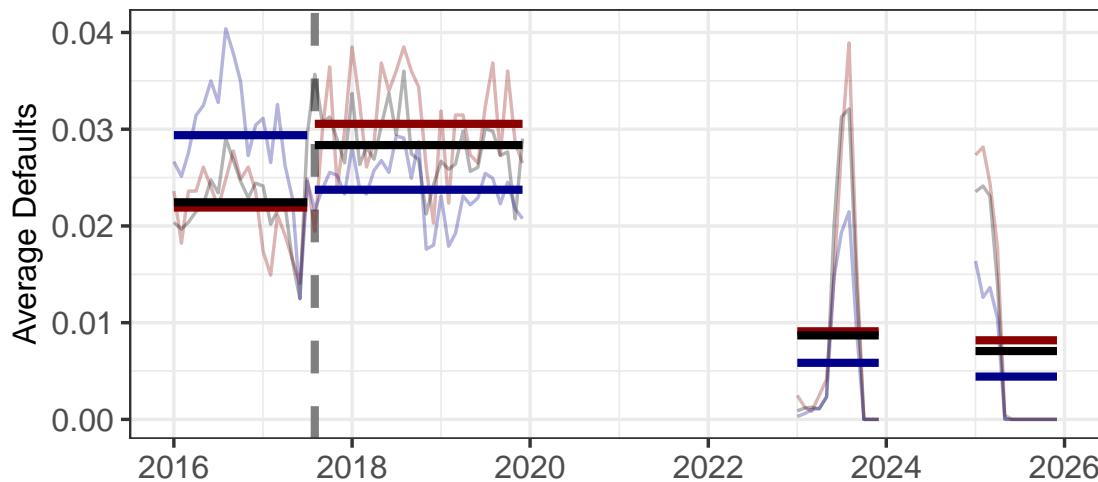


Figure 7. Cohort Averages: Piecewise Fits

Note: The plot shows the average number of default evictions for the three cohorts: Increase-Treated (red), Decrease-Treated (blue), and Controls (black). The raw averages are plotted transparently for years with available data. The piecewise constant fits are overlaid in the same colors. The dashed vertical line is plotted at the time of the policy shock (August 2017).

Following this shock, the estimated average for the Increase-Treated cohort is higher than the Decrease-Treated and Control cohorts, suggesting such tenants experienced the highest average defaults post-August 2017. The Increase-Treated group

⁹¹See also *infra* [Figure C3](#).

average post Aug-2017 is also higher than the pre-Aug 2017 average for any cohort. This is consistent with the tenant cost theory of default, since an increase in distance-to-court is an increased litigation cost which is expected, on average, to increase defaults. But note that the smoothed estimates suggest that average defaults were increasing for the Increase-Treated cohort pre-August 2017: we cannot attribute causality on the basis of high average defaults alone. Therefore, in order to assess causality, we need to use a causal design (a counterfactual model) that specifies counterfactual outcomes for our cohorts.

5.2 Difference-in-Differences (DID) Design

One such counterfactual design—widespread in economics—is the difference-in-differences (DID) design.⁹² This strategy assumes that counterfactual outcomes for the treated group would have evolved “in parallel” to the control group (the *parallel trends* assumption). The DID strategy accounts for differences in baseline outcomes (pre-treatment differences) while controlling for time factors unrelated to the treatment. The results in this section rely on popular methods for DID designs.

In the standard causal inference setting, the researcher first specifies potential outcomes in two states: the treated and untreated (or control) states. The “fundamental problem of causal inference”⁹³ is that we cannot observe individual outcomes in both states simultaneously. However, under randomization, estimating the average treatment effect is straightforward: simply take the difference in average outcomes between the treated and control groups.

Unfortunately, not every causal question can be (or is) addressed by running a randomized experiment due to ethical, legal, financial, or other practical constraints.

⁹²The set-up for the regression discontinuity design (RDD) in Matthew Estes & Kyle Nelson, *Justice Divided, Justice Denied? The Effects of Court Rules on Eviction Outcomes in Los Angeles County* (2025) (unpublished manuscript) is different. Instead of panel data, this method assumes the researcher has access to data on two groups—the treated and control groups—where treatment is determined by an underlying running variable X . This running variable can be many things—age, income, test scores, etc.—but the basic RDD assumes that units above some cutoff C all receive treatment, whereas units below the cutoff C do not receive treatment.

In this setting, the problem of causal inference is that we never observe treated and control units for the same values of the running variable X . This is the more common “sharp” RDD. *But see, e.g.*, Guido W. Imbens and Thomas Lemieux, *Regression Discontinuity Designs: A Guide to Practice*, 142 J. ECONOMETRICS 615 (2008) (for a discussion of the fuzzy RDD). The standard RDD deals with this failure—a *failure of overlap* in the running variable—by making an assumption about what happens across the cutoff C that determines treatment. Specifically, researchers using this design assume that treated and control average outcomes across the cutoff would have evolved continuously.

⁹³Paul W. Holland, *Statistics and Causal Inference*, 81 J. AM. STATISTICAL ASSOCIATION 945 (1986).

Researchers therefore turn to observational studies and methodologies to isolate causal effects. The most popular observational methodology in economics is the difference-in-differences (DID) approach: more than 30% of applied microeconomics working papers mentioned DID or similar designs in 2024.⁹⁴

In the DID design, it is similarly assumed that the researcher has access to data on two groups—the “treated” and “control” groups—over time.⁹⁵ At some point in time, the treated group receives a treatment, whereas the control group does not. The data available includes an outcome variable from before and after the treatment date for both groups. The goal is to estimate the causal effect of treatment on the treated group—called the average treatment effect on the treated (ATT)—after the treatment date. The “fundamental problem of causal inference”⁹⁶ in this setting is that we do not observe untreated outcomes for treated units after the treatment date. The DID method assumes that the average untreated outcome for units that actually receive treatment would have evolved in parallel to the control group average outcome.

In [Figure 8](#), I show how this assumption implies a counterfactual average outcome for the treated group. In this example, the treated group (solid blue line) receives treatment in the year 1950 and the control group (solid red line) never receives treatment. Naively taking differences post-1950 between the treated group average outcome and the control group average outcome would result in an over-estimate of the true treatment effect because the treated and control groups start (and stay) at different baselines in the pre-treatment periods. Indeed, in [Figure 8](#), the treated group average outcome at the beginning of the study period (year 1900) is 5 whereas the control group average outcome is 0.

⁹⁴Paul Goldsmith-Pinkham, *Tracking the Credibility Revolution Across Fields*, Working Paper (May 2024) (Figure 5).

⁹⁵This section details the intuition for simple DID designs, although more complicated (e.g. staggered treatment) designs are possible.

⁹⁶See *supra* Holland (1986).

Difference-in-Differences (DID)

Treated and Control groups

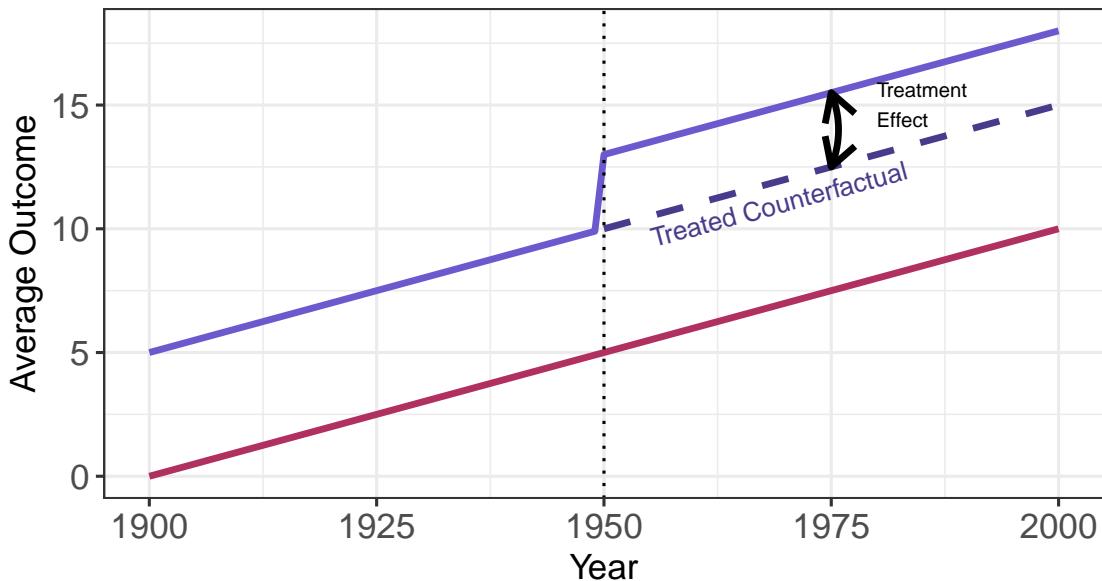


Figure 8. Difference-in-Differences (DID) Method

Note: Average outcomes for the treated and control groups are shown in blue and red, respectively. The dotted vertical line (at 1950) is the treatment date for the Treated group. The dashed blue line is the counterfactual for Treated units: this is the average outcome Treated units would have experienced if they were untreated. The average treatment effect on the treated (ATT) is the difference between the solid and dashed blue lines.

Instead, the DID method assumes the counterfactual outcome for the treated group would've evolved “in parallel” to the control group average. This results in the dashed blue line for the treated group counterfactual. The true average treatment effect on the treated (ATT) is the difference between the observed outcome (solid blue line) and the counterfactual outcome (dashed blue line): it is the average difference in where treated units are versus where they would have been without treatment. This is illustrated in Figure 8 by the double-sided black arrow labeled “Treatment Effect.” Note that it is not a requirement of the methodology that the average treatment effect on the treated be constant in all post-treatment time periods.⁹⁷

5.3 Results: Applying the DID Strategy

Here, I apply the DID strategy to the court expansion policy. I assume that units with changes in distance-to-court would've experienced parallel outcomes to units with zero

⁹⁷The simple constant ATT is for illustration purposes.

changes in distance-to-court. Recall that I consider three cohorts of units: the Control units (zero change in distance-to-court), the Increase-Treated units (positive change in distance-to-court), and the Decrease-Treated units (negative change in distance-to-court). The treatment effect of interest is the average treatment effect on the treated (ATT), which is the difference in expected or average outcomes from treatment versus control for units that actually receive treatment. The DID estimates of the ATT are provided below in [Figure 9](#).

Consider the first set of DID results comparing Increase-Treated units—i.e. units that experienced an increase in distance-to-court—with control units as the comparison group. This means we are using control units to impute counterfactual outcomes for the Increase-Treated units in the counterfactual world where these units do not experience an increase in distance-to-court. In the left panel of [Figure 9](#), I plot the ATT estimates from this comparison.

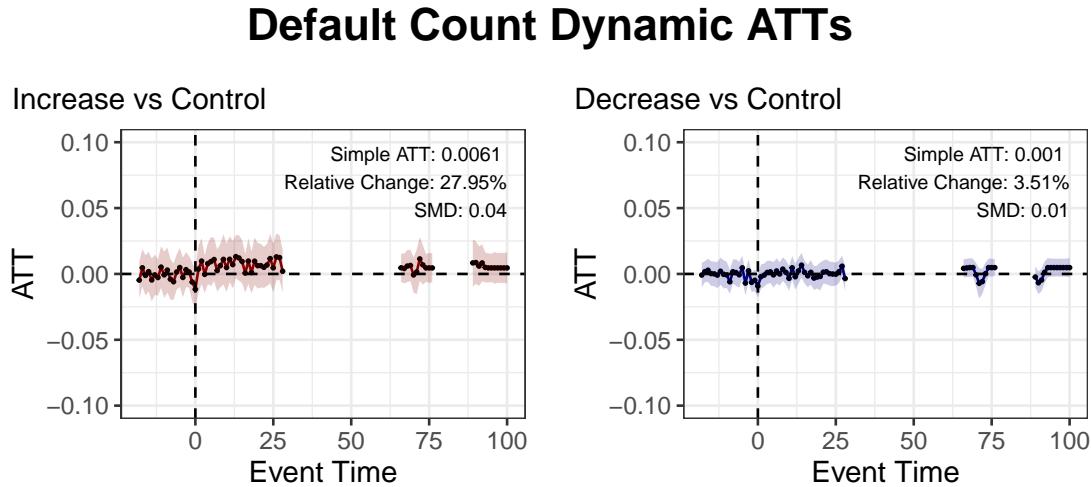


Figure 9. Dynamic DID Estimates: Comparisons with Controls

Note: The panels show estimates of the average treatment effect on the treated for Increase-Treated (left panel) and Decrease-Treated (right panel) units. The Simple ATT aggregates post-treatment ATT estimates as in [Callaway and Sant'Anna \(2021\)](#). The relative change is the percentage change in the number of default evictions relative to the pre-treatment cohort average implied by the ATT estimates. The absolute standardized mean differences (SMDs) suggest small effects under standard rule-of-thumb interpretations.

The point estimates after the court expansion policy (vertical dashed line) are almost all positive: in 50 of 52 post-treatment time periods the ATT point estimates are positive. This means that units with an increased distance-to-court experienced greater default probabilities on average than units with zero change in distance-to-

court following the court expansion policy. However, note that the standard errors are relatively large and include the zero effect for all time periods (dashed horizontal line at 0).

The right panel of [Figure 9](#) repeats this exercise comparing units that are Decrease-Treated with Control units. The post-expansion ATT estimates for the effect on the Decrease-Treated units relative to the Control units are more mixed: 18 of the 52 post-treatment ATT point estimates are negative, but the overall ATT (averaged across post-treatment periods) is small but positive (0.001). This represents a more modest relative change: relative to the average outcome in the pre-treatment periods, the estimated ATTs imply the policy change increased defaults by 3.51% in the post-treatment time periods for Decrease-Treated units. Note, however, that the estimates here too reflect a high degree of uncertainty: most of the post-treatment ATTs are not statistically significant.

In sum, I do not find evidence that court expansion significantly impacted default evictions for early 2017 units using all Increase-Treated and Decrease-Treated units versus the Control group. Although the point estimates are almost always positive in the post-treatment periods for the Increase-Treated cohort, they are not statistically significant. The estimates for the Decrease-Treated ATT are also not significant and the directions are both positive and negative. The aggregate treatment effects (simple ATTs) are also insignificant and positive in both cases.

These comparisons use all units that experienced an increase or decrease in distance-to-court as a treatment cohort. What about units which experienced “large” changes in distance-to-court? We repeat the exercise comparing treated units (those with a change in distance-to-court) versus control units (no change in distance-to-court) by considering only treated units with above-median changes in distance-to-court. The results for this comparison are shown in [Figure 10](#).

Default Count Dynamic ATTs

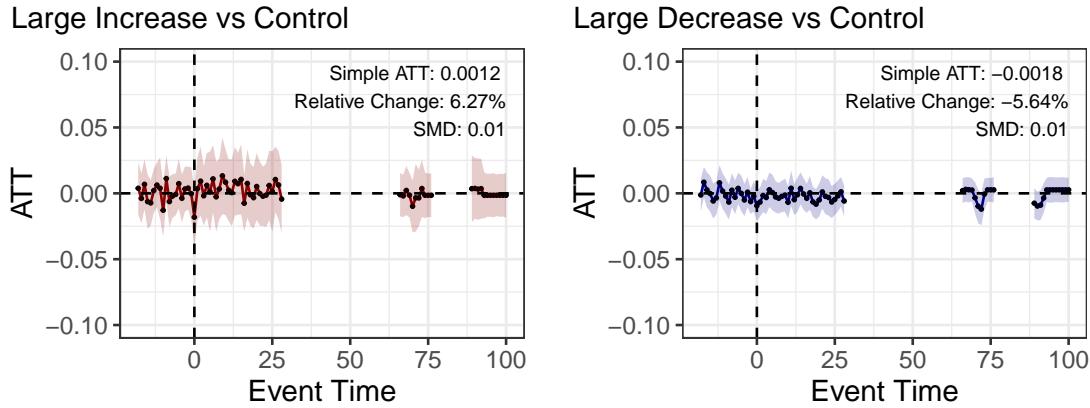


Figure 10. Dynamic DID Estimates: Above-Median Comparisons with Controls

Note: The panels show estimates of the average treatment effect on the treated for Above-Median Increase-Treated (left panel) and Above-Median Decrease-Treated (right panel) units. The Simple ATT aggregates post-treatment ATT estimates as in Callaway and Sant'Anna (2021). The relative change is the percentage change in the number of default evictions relative to the pre-treatment cohort average implied by the ATT estimates. The absolute standardized mean differences (SMDs) suggest small effects under standard rule-of-thumb interpretations.

In this case, the results are subject to increased uncertainty because they utilize a smaller sample,⁹⁸ but the estimates better align with predictions. The simple ATT estimate for units with an above-median increase in distance-to-court is positive and implies treatment (the August 2017 policy) increased defaults by 6.27% relative to the average number of defaults pre-August 2017. By contrast, the simple ATT estimate for units with an above-median decrease in distance-to-court is negative and implies treatment (the August 2017 policy) decreased defaults by 5.64% relative to the average number of defaults pre-August 2017. In other words, there were more default evictions for tenants with a large increase in distance-to-court and fewer defaults for tenants with a large decrease in distance-to-court. Note, however, that the point estimates and aggregate estimates (simple ATTs) are not statistically significant.

6 Discussion & Policy Implications

What lessons to draw from the empirical exercises highlighted in Section 5? Because of uncertainty in the estimates (stemming from relatively small treated cohorts), I first caution against over-generalization. The point estimates are somewhat consistent

⁹⁸This is reflected in the larger confidence intervals on the ATT estimates.

with the tenant cost theory, but we cannot rule out zero effects in most post-treatment time periods or in the aggregate. If legally meaningful effects are limited only to a subset of the population (e.g. those with the highest distance-to-court values), then a larger dataset would be needed to discern the magnitude and direction of the effect.

On the other hand, the results suggest that expanding access via increasing the number of operating courts is not a panacea, at least not if expansion is a modest three court increase in a metropolitan region as large as Los Angeles County. However, the results do not imply that distance-to-court is unimportant or that larger reforms would not find large effects: the results show that this particular August 2017 reform (from 8 to 11 courts) did not significantly reduce default evictions. Indeed, in [Figure 4](#), the changes in the average distance-to-court before and after the policy shock are shown for cases actually filed in the left column courthouse. In some filing courthouses, the average change in the distance-to-court may have been too small to have meaningful effects.

This takeaway accords with much of the procedural intervention literature discussed in [Section 2](#), showing that limited interventions are of limited efficacy.⁹⁹ Larger changes to the eviction system may prove meaningful, but work remains to find cost-effective measures to optimize the legal details of the eviction system. I turn now to discussing some possibilities, including additional work focused on LA County and future research possibilities.

6.1 LA County Regression Discontinuity Results (Estes & Nelson 2025)

One possible strategy is explored in Estes & Nelson (2025),¹⁰⁰ where we examine the boundaries of the spatial map in LA County to test whether how the map is drawn creates meaningful differences in tenant cost structures. The idea is that, unlike the Fedex or Amazon delivery system, legal assignment mechanisms are not designed, tested, and regularly optimized. Although the designers of legal rules and institutions may intend to improve welfare (or at least do no harm), the nature of the legal enterprise—especially judicial decision-making—is such that rules often need to be fashioned without empirical evidence and are, therefore, non-optimal.¹⁰¹

⁹⁹Some interventions, moreover, may backfire. *See supra* discussion of regressive effects of expanding small claims amounts.

¹⁰⁰Matthew Estes & Kyle Nelson, *Justice Divided, Justice Denied? The Effects of Court Rules on Eviction Outcomes in Los Angeles County* (2025) (unpublished manuscript)

¹⁰¹Accord Jack Goldsmith & Adrian Vermeule, *Empirical Methodology and Legal Scholarship*, 69 U. CHI. L. REV. 153 (2002) (“One reason (but not the only one) why legal scholars sometimes trade accuracy for relevance and timeliness is their close connections to governmental institutions,

Identifying rules for improvement with empirical study can assist legal and policy decision-makers to better fashion alternative rules, especially when it comes to the important task of simulating counterfactual policies (e.g. redrawing maps).¹⁰²

This companion paper studies the spatial aspect the case assignment mechanism and suggests regions where alternative maps may be most effective. Empirical evidence therein suggests statistically significant differences in default probabilities near the boundaries of specific LA County eviction court districts. Using spatial variation stemming from the discontinuous assignment of cases to eviction courthouses, the paper estimates the effects of eviction procedures on tenant outcomes locally at courthouse boundaries.¹⁰³ The main contribution of the paper is to show that, at the boundary of several eviction courthouse districts, there are statistically significant differences in the default probability for tenants on one side of a courthouse boundary versus another.¹⁰⁴

Specifically, we test whether units located nearby experience differences in default probability due to assignment to one court versus another. Formally, this type of study is a spatial regression discontinuity design, which takes advantage a spatial policy that creates borders between two (or more) regions. A local causal effect is estimated by comparing cases along a policy border that receive different treatments. The intuition is that cases located nearby—but across some quasi-random policy boundary—have “similar” observed and unobserved characteristics. Under this assumption, differences between nearby units are therefore attributable to the difference in the spatial “treatment” variable.

To illustrate graphically the types of comparisons the method makes to obtain causal estimates, consider, for example, the rental units near the Compton and Norwalk boundary in LA County. In [Figure 11](#), I plot the Compton and Norwalk court

especially courts, that have to make decisions in the short term under conditions of empirical uncertainty.”).

¹⁰²The idea of redrawing eviction assignment maps and simulating outcomes is not unlike simulating maps in the gerrymandering literature, a subject of interest and study for election law scholars and other social scientists.

¹⁰³*Cf.* Collinson et. al. (2024) (using spatial comparisons from nearby zip codes).

¹⁰⁴Here, I also show that the gap obtains also for another outcome variable: money judgments. See [Figure B2](#) (estimating how large courthouse assignment effects are in monetary terms for defaulting tenants near courthouse boundaries). Because defaulting tenants are liable for unpaid rent, courthouse assignment can effect the average monetary judgments owed landlords near the courthouse boundary. The results shown below in [Figure B2](#) provide robust estimates of the LATE in the bottom-right table for each courthouse pair, along with robust CIs. The CIs restrain the magnitude of the effects to around 1-2 months rent. Because these comparisons only use addresses with observed default evictions, they are robust to issues stemming from assessor-imputed outcomes for unobserved units.

districts in red and blue, resp. Addresses with at least one default eviction that are within 5km of the Compton-Norwalk boundary (yellow boundary) are plotted below.

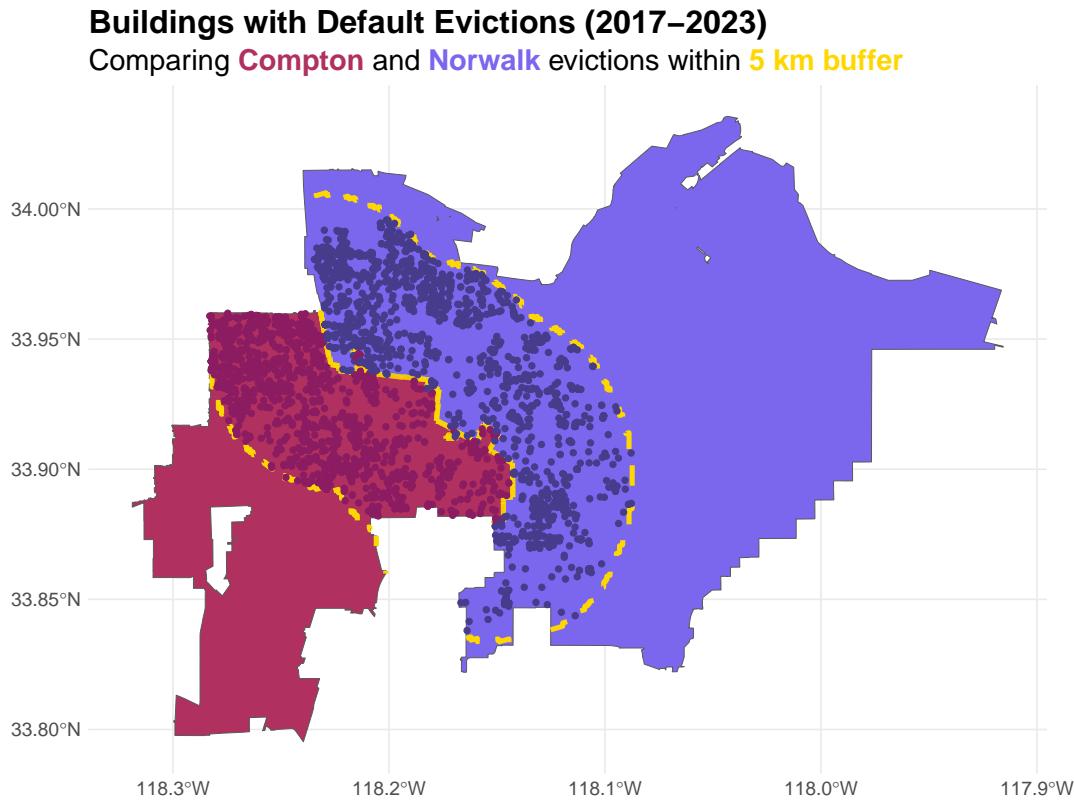


Figure 11. Compton & Norwalk Eviction Districts

Note: Defaults within 5km of the courthouse boundary (solid-yellow line) are shown as red (Compton courthouse) and blue (Norwalk courthouse) points.

We compare only units near the boundary because they are expected to be similar the closer we get to the boundary. Under the assumption that units near the boundary are, on average, “sufficiently similar,” the differences in the probability of default eviction are attributable to being assigned to the Compton courthouse rather than the Norwalk courthouse. In this example, being assigned to the Compton courthouse rather than the Norwalk courthouse increases the probability of default eviction by 8.81¹⁰⁵ percentage points. See Appendix B for results for seven different courthouse pairs.¹⁰⁶ In some cases, there is no significant difference at the courthouse boundary,

¹⁰⁵The robust confidence interval for this courthouse boundary is (7.05, 10.56) percentage points. These estimates are obtained from using standard robust RDD tools. See Matthew Estes & Kyle Nelson, *Justice Divided, Justice Denied? The Effects of Court Rules on Eviction Outcomes in Los Angeles County* (2025) (unpublished manuscript) for further details.

¹⁰⁶Reproducing results from Matthew Estes & Kyle Nelson, *Justice Divided, Justice Denied?*

whereas in other cases there are large, significant effects.¹⁰⁷ In those regions where large local effects appear persistent, “re-optimizing” the court assignment map may help reduce default evictions. In the long-term, adaptive court assignment policies—with periodic assessment, analysis, and adjustment (if warranted)—may help alleviate the access-to-justice problem.

6.2 Other Research: Transportation & Structural Reforms

Another possibility is investment in transportation infrastructure. Although I am unaware of existing datasets on changes to the transportation network in LA County, future work might look at how transportation and commuting costs—as opposed to distance-as-cost—impacts tenants. These variables are all likely to be highly correlated, but additional survey research on tenant commuting patterns could be helpful. Potential avenues include studying how tenants get to court, how far their jobs are from courts, and what methods of transportation they use in a sprawling urban city like Los Angeles.¹⁰⁸

Finally, I conclude by observing that further research into long-term strategies to reduce evictions is needed. Trying to solve the eviction problem only after tenants receive an eviction notice may be too late. The “disease” of high rent is left untreated if a broader strategy to reform housing markets—especially to increase housing supply—is not undertaken. Fortunately, advocates, voters, and policymakers seem increasingly willing to embrace an abundance agenda in housing. In time, researchers will have new data to monitor the impact of such reforms on rental markets. As policy changes unfold, eviction researchers should monitor how eviction outcomes respond to structural housing reform.

The Effects of Court Rules on Eviction Outcomes in Los Angeles County (2025) (unpublished manuscript).

¹⁰⁷To examine mechanisms, Matthew Estes & Kyle Nelson, *Justice Divided, Justice Denied? The Effects of Court Rules on Eviction Outcomes in Los Angeles County* (2025) (unpublished manuscript) also explores whether any differences remain after controlling for distance-to-court: although there is greater uncertainty in the estimation because conditioning on distance-to-court estimation utilizes smaller sample sizes, we find that the confidence bands for the conditional effects contain zero. In other words, the data used in the spatial RDD is consistent with distance being the primary mechanism determining defaults eviction probability.

¹⁰⁸Potentially the best way to get at this possibility would be to use cell-tracking data to pinpoint exact travel distances or times to court from tenant last location (e.g. job).

References

- B. Callaway and P. H. Sant'Anna. Difference-in-differences with multiple time periods. *Journal of econometrics*, 225(2):200–230, 2021.
- 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.

APPENDICES

A Appendix A: Types of Reforms

Appendix A includes a table summarizing two approaches to combat evictions: procedural and structural reforms. Procedural reforms tend to focus on making the eviction process “fair” for tenants. Because tenants often face a large resource disadvantage in eviction cases, procedural reforms aim to “level the playing field” for tenants in cases against better-resourced landlords. Procedural policy reforms might include, for example, allowing longer tenant response times, permitting remote court attendance, reducing filing fees, and providing publicly-funded tenant counsel.¹⁰⁹ Procedural proposals prioritize helping tenants *after* they’ve received an eviction notice.¹¹⁰

Structural reforms, by contrast, aim to address the underlying causes of eviction. Because non-payment of rent is the primary reason for eviction, structural reforms tend to focus on reducing rent and housing prices. Because of the large impact of housing supply on prices,¹¹¹ the goal is usually (but not always) to increase the available stock of rental housing. Structural reforms may include, for example, subsidizing the building of affordable housing units, building public housing, increasing housing vouchers, or changing income thresholds to receive rental assistance. Structural proposals prioritize helping tenants *before* they’ve received an eviction notice.

¹⁰⁹The last proposal is sometimes referred to as “civil *Gideon*”, a reference to *Gideon v. Wainwright* (1963), the landmark Supreme Court decision requiring states to provide defense counsel to indigent criminal defendants.

¹¹⁰See, e.g., D. James Greiner, Cassandra Wolos Pattanayak, and Jonathan Philip Hennessy, *How Effective Are Limited Legal Assistance Programs? A Randomized Experiment in a Massachusetts Housing Court* (2012); Mike Cassidy and Janet Currie, *The Effects of Legal Representation on Tenant Outcomes in Housing Court: Evidence from New York City’s Universal Access Program*, 222 J. PUBLIC ECONOMICS 104844 (2023).

¹¹¹See Nathaniel Baum-Snow and Gilles Duranton, *Housing Supply and Housing Affordability*, NBER Working Paper (2025) (discussing extensive literature on housing supply and prices).

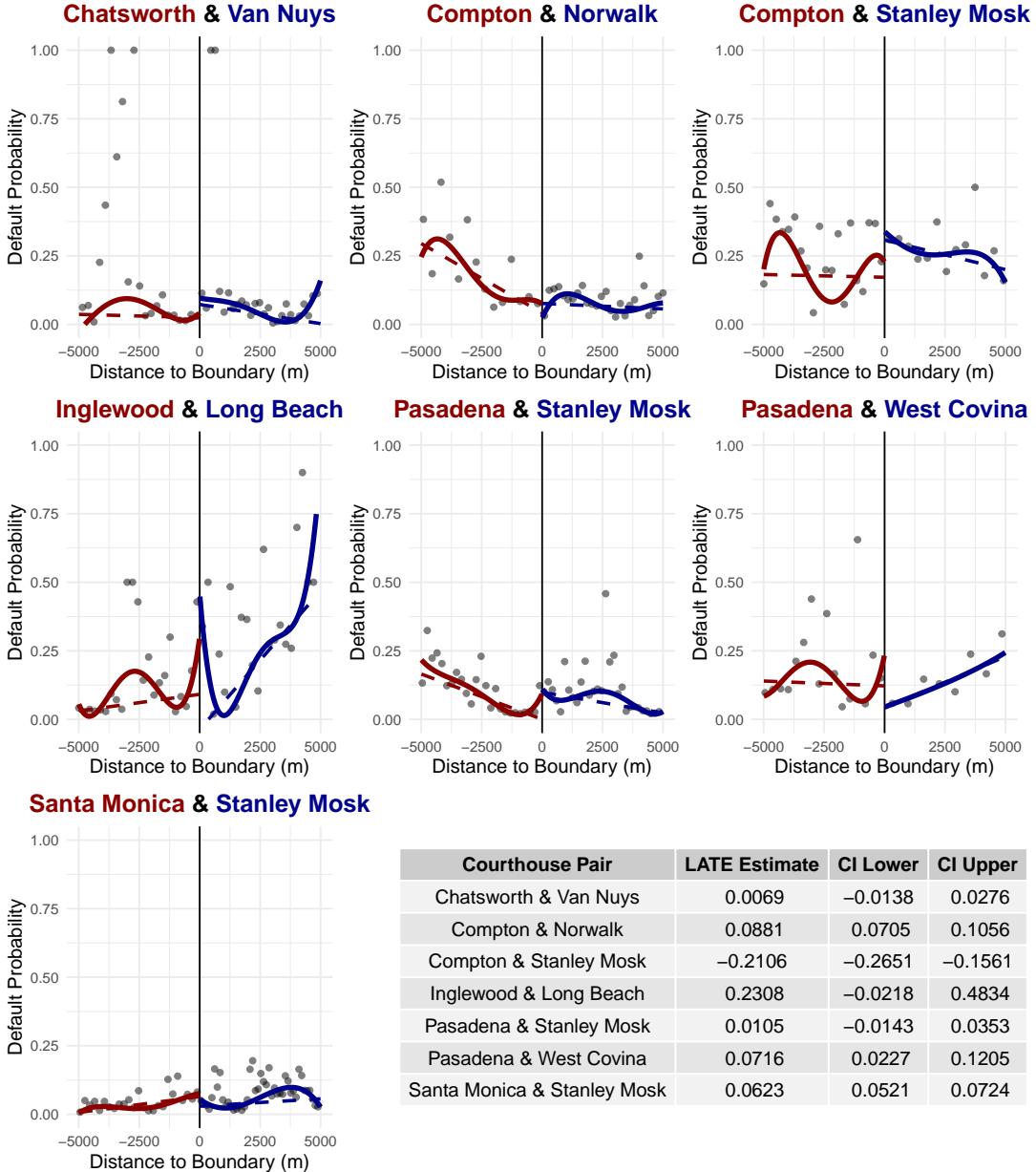
Characteristic	Procedural Reforms	Structural Reforms
Primary Goal	Fair process	Eliminate root causes
Policy Focus	Alter legal proceedings	Reduce rent burden and increase affordability
Intervention Timing	After eviction notice	Before eviction notice
Mechanisms	Legal aid, court procedures, fee reductions	Supply-side housing policy, subsidies, vouchers
Typical Examples	Longer response times, remote hearings, public counsel (<i>Civil Gideon</i>)	Public housing, expand vouchers, eligibility thresholds

Appendix Table A1. Comparison of Procedural and Structural Eviction Reforms

B Appendix B: RDD Study Plots (Estes & Nelson 2025)

LATE Results by Courthouse Pairs

Estimates at the Boundary for Robust Bandwidth

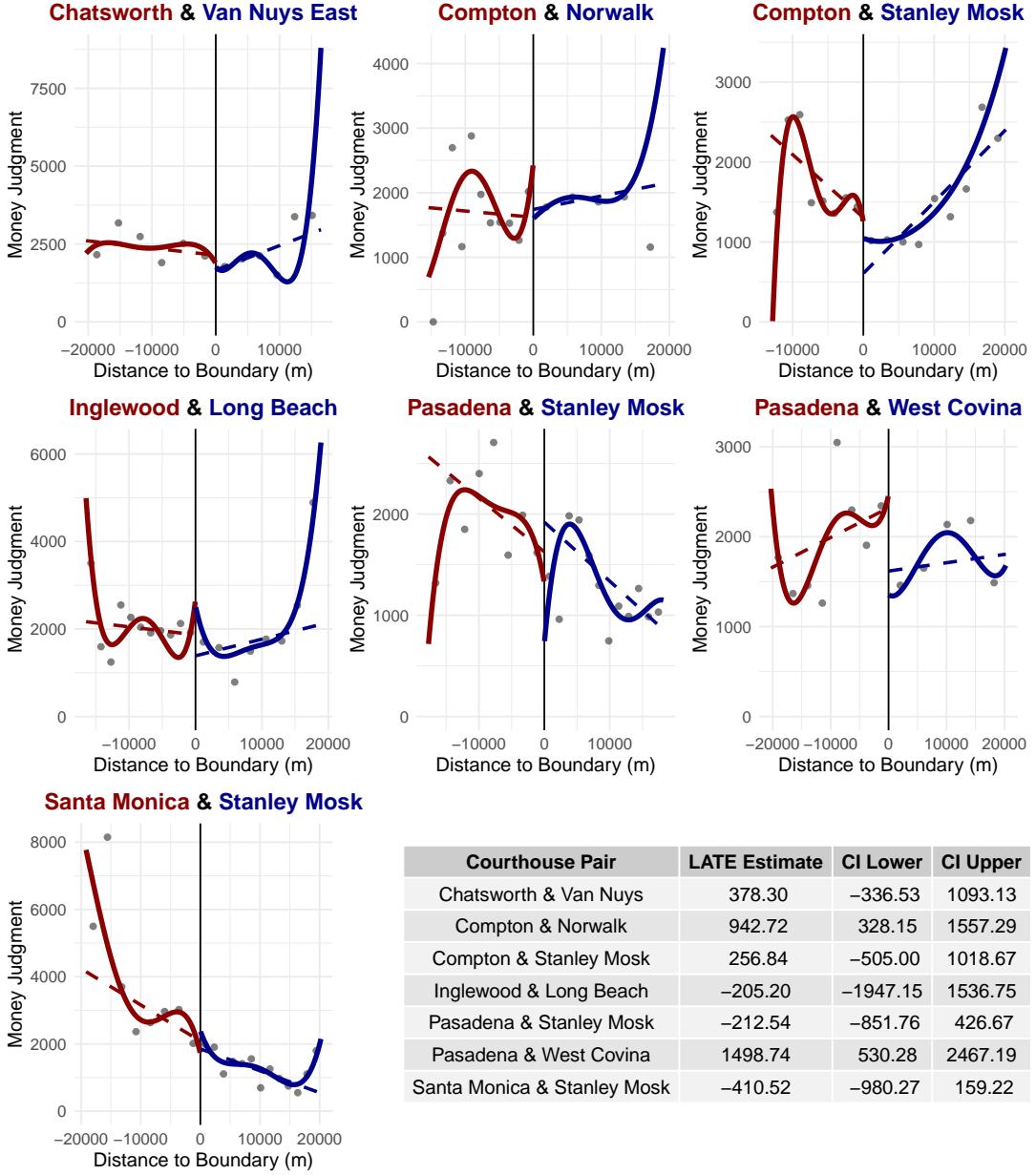


Appendix Figure B1. LA County Default Eviction Probability

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

LATE Money Judgment Results

Estimates at the Boundary by Courthouse Pairs



Appendix Figure B2. LA County Money Judgments

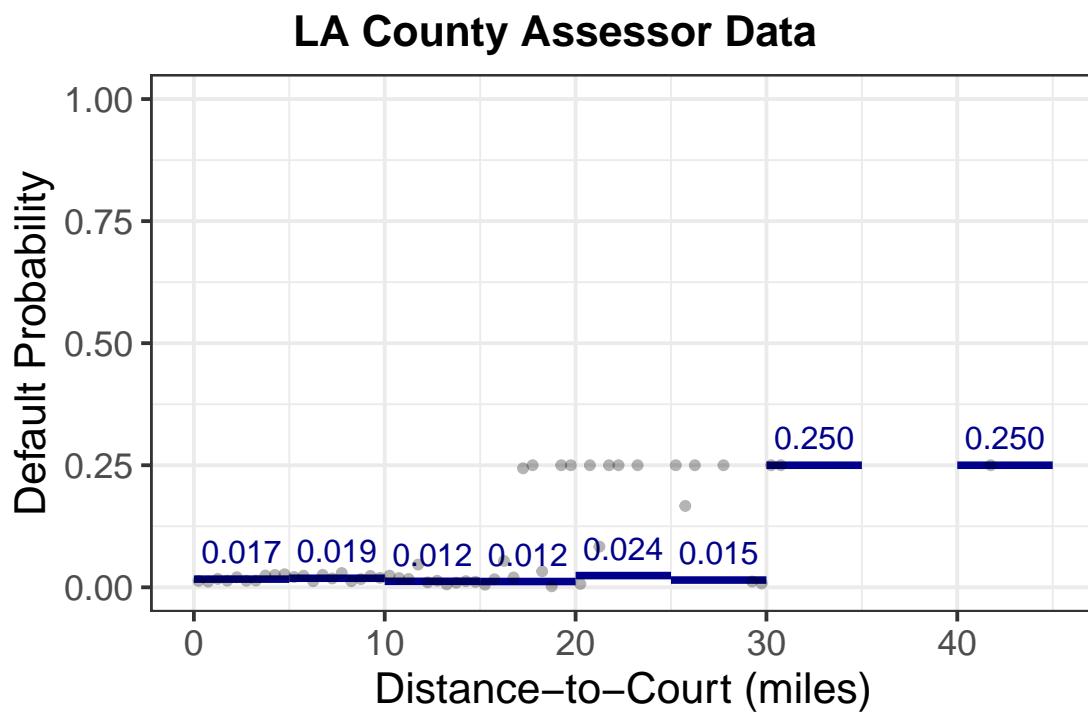
Note: The LATE estimates on money judgment amounts ($\hat{\tau}_{C,m}$) at each courthouse pair boundary use the optimal bandwidth selection procedure in the `rdrobust` package (Calonico et al., 2023). The global quartic polynomial (solid line) and global linear (dashed line) fits are plotted for each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

C Appendix C: Additional Results

Appendix C includes additional results plots, focusing mostly on court expansion DID estimates.

C.1 Reduced Form

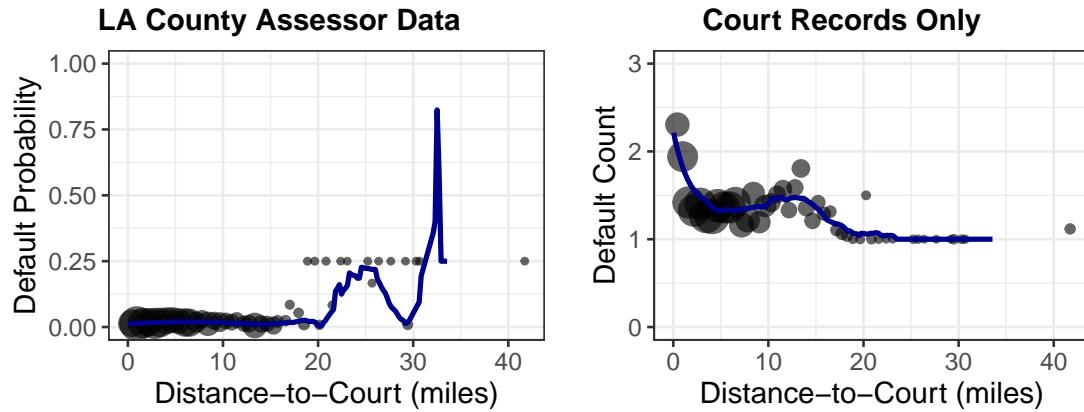
These plots are discussed in text above. They show reduced form relationships using assessor data and court records.



Appendix Figure C1. Reduced Form (LA County Assessor): 5-mile Binned Averages

Note: The blue lines are binned averages (every 5 miles) and the transparent points show default probabilities every 0.5 miles.

Local Linear Regressions (with Uniform Kernel)



Appendix Figure C2. Reduced Form Relationships: Default Probability & Default Counts

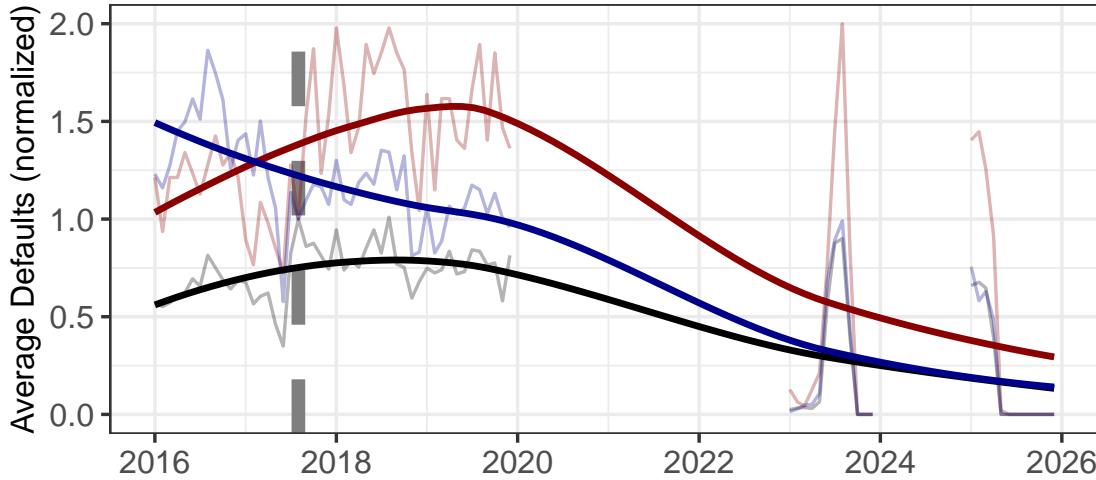
Note: The blue curves are local linear regression estimates (with a uniform kernel and bandwidth 5km) of the relationship between distance-to-court and default probability (left panel) or default counts (right panel).

C.2 Cohort Trends: Increased, Decreased, and Control

The plot below shows average defaults with a LOESS smoothed trend across all time periods for each treatment cohort: the Increase-Treated group (red), the Decrease-Treated group (blue), and the Control group (black). The raw averages are normalized individually for each cohort, so the following plot is not for inter-cohort comparisons but to show trends for each cohort.

Average Defaults by Cohort

Increased, Control, and Decreased – LOESS Smoothed Trends



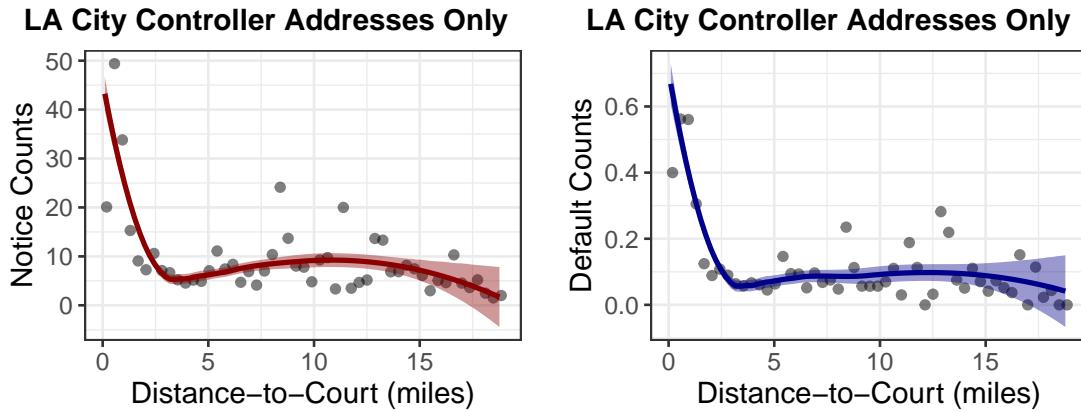
Appendix Figure C3. Cohort Averages

Note: The plot shows the average number of default evictions for the three cohorts: Increase-Treated (red), Decrease-Treated (blue), and Controls (black). The raw averages are plotted transparently (and normalized to one in August 2017) for years with available data. The LOESS-estimated smooth trends are overlaid in the same colors. The dashed vertical line is plotted at the time of the policy shock (August 2017).

C.3 LA City Controller Data Only Results

To address potential concerns with using either assessor-based addresses as the population of rental addresses or only addresses with at least one observed default, I consider here using new data from the LA City Controller's Office. A rule change in 2023 mandated that all landlords in LA City record eviction notices with the City Controller's Office. The data includes address information for each eviction notice, allowing me to identify the universe of apartment buildings at-risk of eviction or default eviction. Using only these addresses in LA City, I reproduce the main-text results: reduced-form relationships and dynamic DID event-study type plots.

LA City Controller Averages (2023–2025)

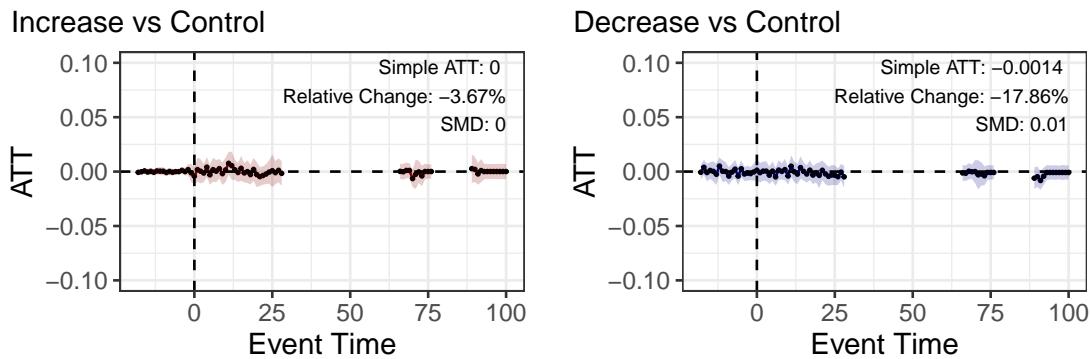


Appendix Figure C4. Reduced Form (LA City Controller Data)

Note: The left panel shows the smoothed LOESS estimates of the average number of notice counts as a function of distance-to-court. The right panel shows the smoothed LOESS estimates of the average number of defaults as a function of distance-to-court.

Default Count Dynamic ATTs (2016–2025)

LA City Controller Addresses Only

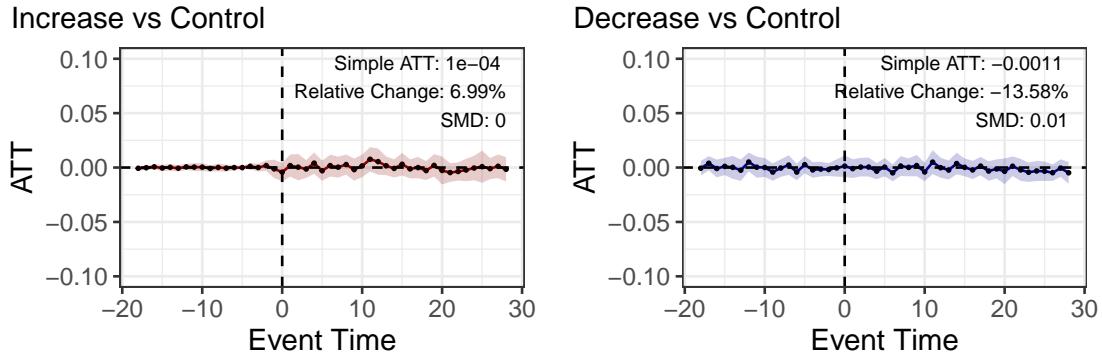


Appendix Figure C5. Dynamic DID Estimates (LA City Controller Addresses Only)

Note: The panels show estimates of the average treatment effect on the treated for Increase-Treated (left panel) and Decrease-Treated (right panel) units. The Simple ATT aggregates post-treatment ATT estimates as in Callaway and Sant'Anna (2021). The relative change is the percentage change in the number of default evictions relative to the pre-treatment cohort average implied by the ATT estimates. The absolute standardized mean differences (SMDs) suggest small effects under standard rule-of-thumb interpretations.

Default Count Dynamic ATTs (pre-2020)

LA City Controller Addresses Only



Appendix Figure C6. Dynamic DID Estimates Pre-2020 (LA City Controller Addresses Only)

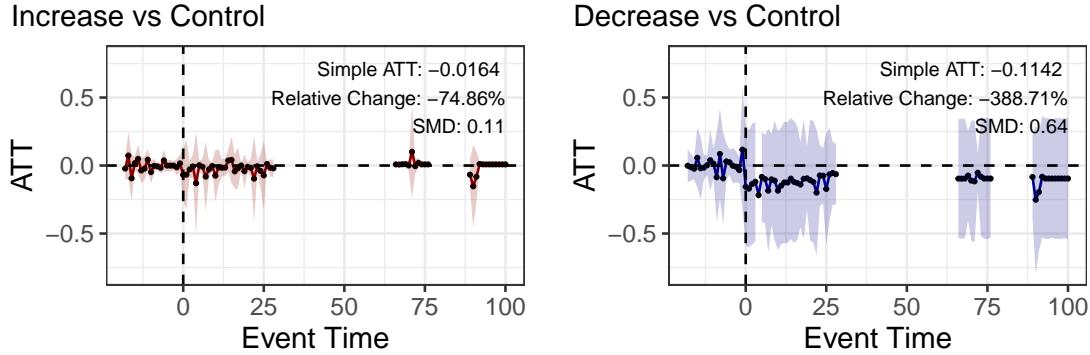
Note: The panels show estimates of the average treatment effect on the treated for Increase-Treated (left panel) and Decrease-Treated (right panel) units. The Simple ATT aggregates post-treatment ATT estimates as in Callaway and Sant'Anna (2021). The relative change is the percentage change in the number of default evictions relative to the pre-treatment cohort average implied by the ATT estimates. The absolute standardized mean differences (SMDs) suggest small effects under standard rule-of-thumb interpretations.

C.4 Assessor Unit-Weighted Results

I also include results with outcomes weighted by the number of apartment units. Using the LA Assessor data, I match addresses in the eviction dataset to assessment data on how many units there are in each building. The exercise is complicated from a data perspective, as some rental units may be empty or matches to assessment data may be subject to assessor recording or matching error. But the DID-style estimates allow us to estimate how the court expansion affected tenants in all units living at the addresses in the eviction dataset. The weighted estimates are produced below for all years and for the pre-2020 years separately. The results are subject to very large uncertainty (much larger SEs) and insignificant in both the point estimates and the aggregate. Moreover, the direction of the effect does not align with expectations for the Increase versus Control comparisons.

Default Count Dynamic ATTs

Assessor Unit–Weighted

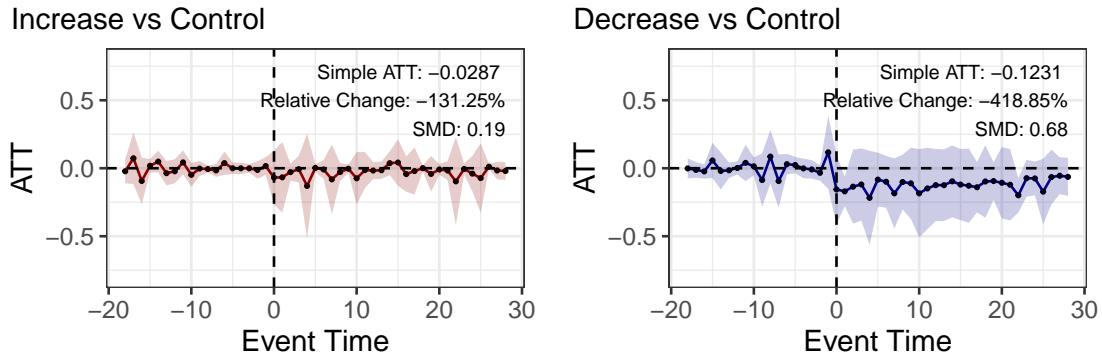


Appendix Figure C7. Dynamic DID Estimates (Assessor Unit-Weighted)

Note: The panels show estimates of the average treatment effect on the treated for Increase-Treated (left panel) and Decrease-Treated (right panel) units. The Simple ATT aggregates post-treatment ATT estimates as in Callaway and Sant'Anna (2021). The relative change is the percentage change in the number of default evictions relative to the pre-treatment cohort average implied by the ATT estimates. The absolute standardized mean differences (SMDs) suggest small and medium effects, resp., under standard rule-of-thumb interpretations.

Default Count Dynamic ATTs (pre-2020)

Assessor Unit–Weighted



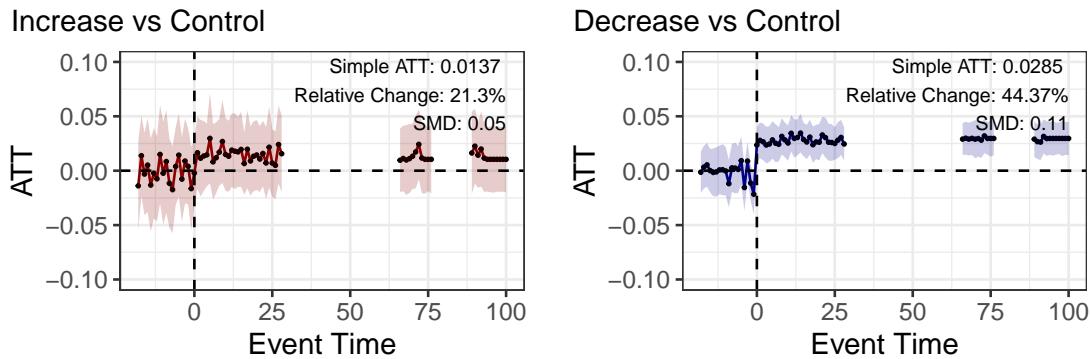
Appendix Figure C8. Dynamic DID Estimates Pre-2020 (Assessor Unit-Weighted)

Note: The panels show estimates of the average treatment effect on the treated for Increase-Treated (left panel) and Decrease-Treated (right panel) units. The Simple ATT aggregates post-treatment ATT estimates as in Callaway and Sant'Anna (2021). The relative change is the percentage change in the number of default evictions relative to the pre-treatment cohort average implied by the ATT estimates. The absolute standardized mean differences (SMDs) suggest small and medium effects, resp., under standard rule-of-thumb interpretations.

C.5 Pre-Aug 2017 Buildings Only Results

Finally, to address potential bias from including all buildings with observed evictions in the main analysis, I include results for only those buildings with observed default evictions pre-Aug 2017. The results for the Increase-Treated and Large Increase-Treated versus Control group are both insignificant; moreover, the Large Increase ATTs are mostly negative, which does not align with the predicted effect: those buildings with an increase in distance-to-court are expected to have increased defaults. Conversely, the Decrease-Treated and Large Decrease-Treated comparisons with the Control group are significant, but neither effect aligns with expectations: the point estimates and aggregate simple ATTs are all positive. The results reinforce the conclusions in the main body of the paper: either there is large uncertainty (Increase comparisons) or the results do not align with expectations (Decrease comparisons).

Default Count Dynamic ATTs Pre-Aug 2017 Buildings Only

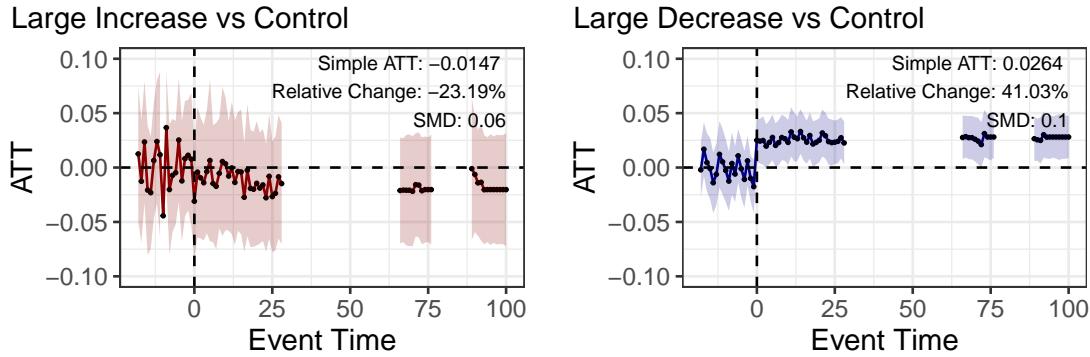


Appendix Figure C9. Dynamic DID Estimates (pre-Aug 2017 Buildings Only)

Note: The panels show estimates of the average treatment effect on the treated for Increase-Treated (left panel) and Decrease-Treated (right panel) units. The Simple ATT aggregates post-treatment ATT estimates as in Callaway and Sant'Anna (2021). The relative change is the percentage change in the number of default evictions relative to the pre-treatment cohort average implied by the ATT estimates. The absolute standardized mean differences (SMDs) suggest small effects under standard rule-of-thumb interpretations.

Default Count Dynamic ATTs

Pre–Aug 2017 Buildings Only

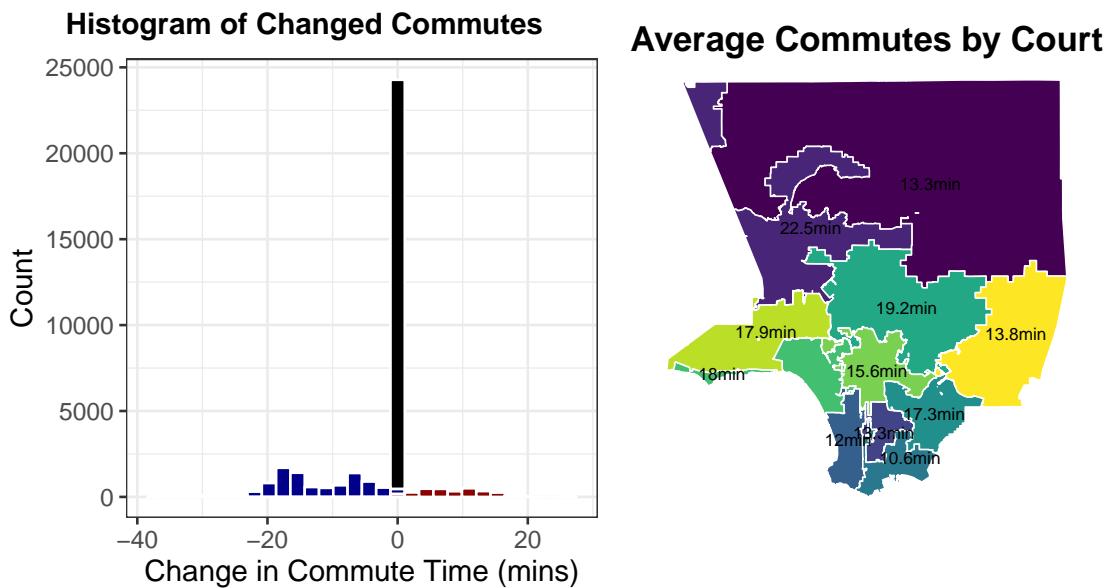


Appendix Figure C10. Dynamic DID Estimates: Above-Median Comparisons (pre-Aug 2017 Buildings Only)

Note: The panels show estimates of the average treatment effect on the treated for Increase-Treated (left panel) and Decrease-Treated (right panel) units. The Simple ATT aggregates post-treatment ATT estimates as in Callaway and Sant'Anna (2021). The relative change is the percentage change in the number of default evictions relative to the pre-treatment cohort average implied by the ATT estimates. The absolute standardized mean differences (SMDs) suggest small effects under standard rule-of-thumb interpretations.

D Appendix D: Commute Times

Appendix D includes additional findings using commute times rather than distance-to-court as the treatment variable of interest. Commute times were calculated for each address using the Mapbox API.



Correlation: Distance-to-Court and Commute Time

Overall Correlation = 0.848

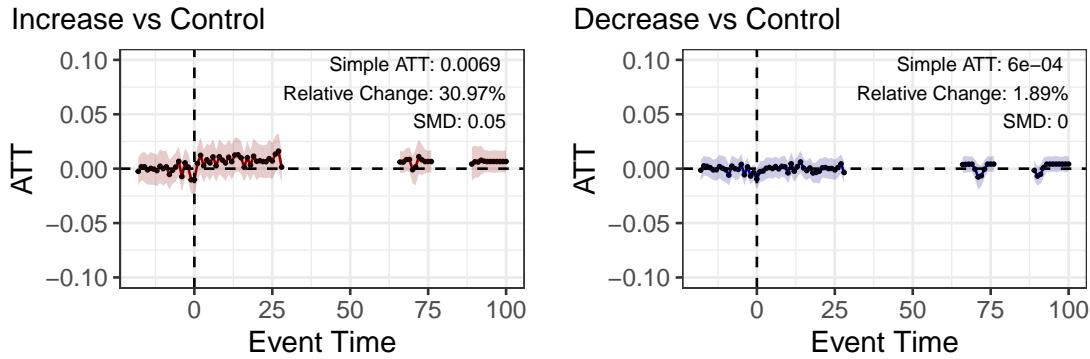
Filing Courthouse	Correlation	N	Filing Courthouse	Correlation	N
Antelope Valley	0.965	3809	Pasadena	0.918	6677
Chatsworth	0.947	1715	Pomona	0.948	2082
Compton	0.871	1926	Santa Monica	0.925	4452
Inglewood	0.953	2229	Stanley Mosk	0.934	11080
Long Beach	0.914	7342	Van Nuys East	0.938	3327
Norwalk	0.963	5771	West Covina	0.765	2739

Appendix Figure D1

Note: The top-left panel shows the histogram of changes in commute times following the August 2017 policy shock. The top-right panel maps the average commutes by court district under the post-August 2017 assignment map. The bottom table shows the correlation between distance-to-court and commute times for each observed filing courthouse (overall corr. ≈ 0.848).

DID results are shown below. As in the other cases, the results are not significant, do not align with expectations as to the sign of the effect (e.g. Decrease-Treated and Large Decrease-Treated units have positive aggregate simple ATTs), or both. Note as well the small absolute standardized mean differences (SMDs) in each panel.

Default Count Dynamic ATTs Commute Time Treatment Encoding

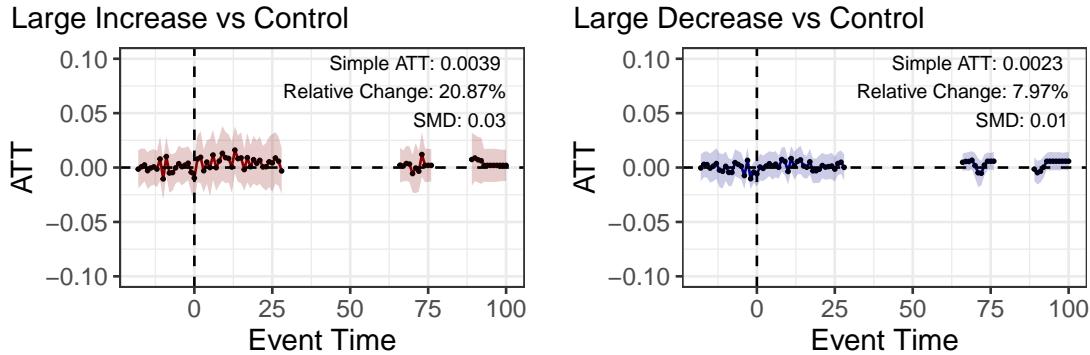


Appendix Figure D2. Dynamic DID Estimates: Comparisons with Controls (Commute Times)

Note: The panels show estimates of the average treatment effect on the treated for Increase-Treated (left panel) and Decrease-Treated (right panel) units. The Simple ATT aggregates post-treatment ATT estimates as in Callaway and Sant'Anna (2021). The relative change is the percentage change in the number of default evictions relative to the pre-treatment cohort average implied by the ATT estimates. The absolute standardized mean differences (SMDs) suggest small effects under standard rule-of-thumb interpretations.

Default Count Dynamic ATTs

Commute Time Treatment Encoding



Appendix Figure D3. Dynamic DID Estimates: Above-Median Comparisons with Controls (Commute Times)

Note: The panels show estimates of the average treatment effect on the treated for Large Increase-Treated (left panel) and Large Decrease-Treated (right panel) units. The Simple ATT aggregates post-treatment ATT estimates as in Callaway and Sant'Anna (2021). The relative change is the percentage change in the number of default evictions relative to the pre-treatment cohort average implied by the ATT estimates. The absolute standardized mean differences (SMDs) suggest small effects under standard rule-of-thumb interpretations.

E Appendix E: Relaxing Parallel Trends

[Appendix E](#) includes additional results which weaken the key identification assumption. Meta-analyses of existing DID research suggests violations of parallel trends is common and requires validation, sensitivity analysis, or relaxation.¹¹² Although there are a few ways to relax the parallel trends assumption, I examine here a Manski-style partial identification approach following Manski & Pepper (2018)¹¹³ and Estes & Clark (2025).¹¹⁴ This approach easily accommodates a form of sensitivity analysis to a tuning parameter, which I discuss below.

To begin, I specify the treatment effect estimand of interest: the *average treatment effect on the treated* (“ATT”) for units in two treatment cohorts $\vec{k} = (k_1, k_2, \dots)$ and $\vec{k}' = (k'_1, k'_2, \dots)$. This notation for treatment \vec{k} says that k_1 is the treatment level received at time 1, k_2 the treatment level at time 2, etc. The average treatment effect in time t on units treated with \vec{k} :

$$ATT(t, \vec{k}, \vec{k}') = \mathbb{E}[Y_{it}(\vec{k}) - Y_{it}(\vec{k}') | \vec{K}_i = \vec{k}]$$

This is the average treatment effect from switching to treatment \vec{k}' for units on treatment \vec{k} at time t . The identification problem is that $Y_{it}(\vec{k}')$ is unobservable for units with observed treatment $\vec{K}_i = \vec{k}$.

For two distinct treatment histories \vec{k} and \vec{k}' , let the first time period the treatments diverge (i.e. do not agree) be denoted $T_{div} = \text{argmin}_t(k_t \neq k'_t)$. I use information from the pre-divergence periods (i.e. time periods before T_{div}) and the following assumption to impute counterfactual outcomes.

Assumption 1. [Average Bounded Deviation] *Let $T_{div} = \arg\min_t(k_t \neq k'_t)$ for distinct treatments \vec{k} and \vec{k}' . Then the following holds for each i , $t \geq T_{div}$, any (\vec{k}, \vec{k}') pair, and some $C \in \mathbb{R}_+$:*

$$\left| \mathbb{E}[Y_{it}(\vec{k}') | \vec{K}_i = \vec{k}] - \mathbb{E}[Y_{it}(\vec{k}') | \vec{K}_i = \vec{k}'] \right| \leq C \cdot \max_{t < T_{div}} \left| \mathbb{E}[Y_{it} | \vec{K}_i = \vec{k}] - \mathbb{E}[Y_{it} | \vec{K}_i = \vec{k}'] \right|$$

where $C = C(t, \vec{k}, \vec{k}')$ can depend on the time period and both treatments.

¹¹²See Albert Chiu, Xingchen Lan, Ziyi Liu, and Yiqing Xu, *Causal Panel Analysis under Parallel Trends: Lessons from a Large Reanalysis Study*, AMERICAN POLITICAL SCIENCE REVIEW (2025).

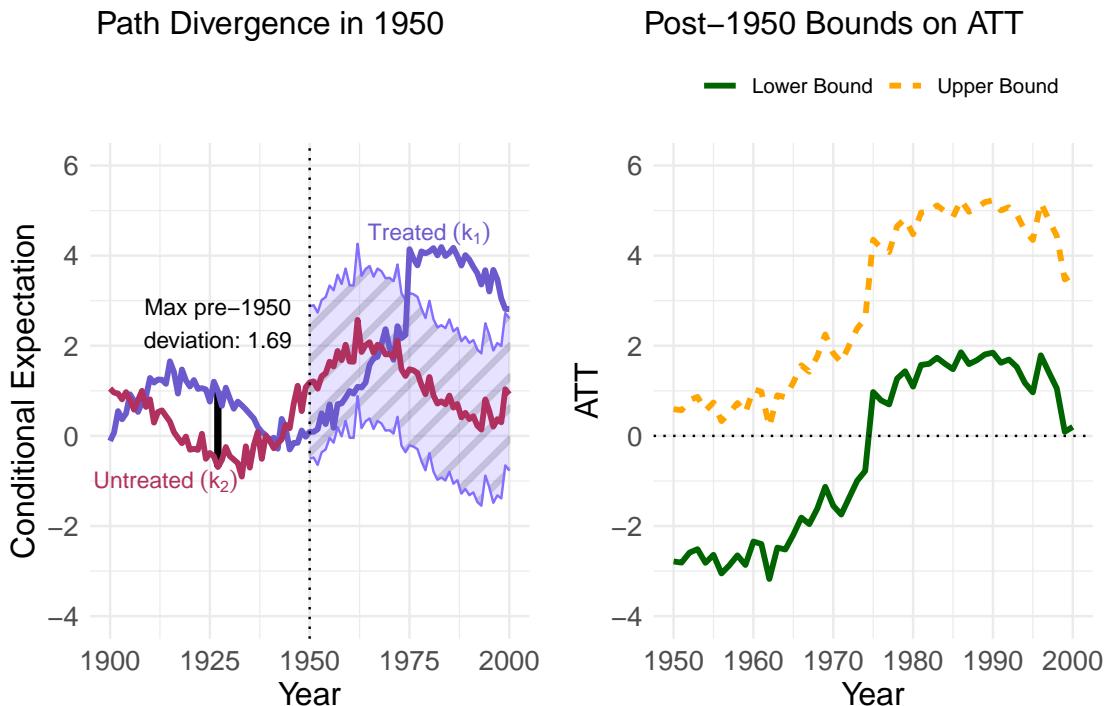
¹¹³Charles F. Manski and John V. Pepper, *How Do Right-to-Carry Laws Affect Crime Rates? Coping with Ambiguity Using Bounded-Variation Assumptions*, 100 REV. ECONOMICS & STATISTICS 232 (2018).

¹¹⁴Matthew Estes and Ransi Clark, *Courting the Academy: The Judicial Role in Popularizing Legal Scholarship*, Working Paper (2025).

This assumption says the counterfactual average outcome from treating with \vec{k}' instead of \vec{k} for units with observed treatment $\vec{K}_i = \vec{k}$ is “near” the observed outcome for units with treatment \vec{k}' . Specifically, the counterfactual average for the \vec{k} -treated group is within C times the maximum absolute difference in means for units on the two treatments before they diverge in time.

The method is illustrated graphically below in [Figure E1](#). In the left panel, the two lines are average outcomes for Treated (blue) and Untreated (red) units. The black-dotted vertical line is the path divergence time period, which in this example is 1950. The blue-striped region is the counterfactual region for blue Treated units: this is where counterfactual outcomes for Treated units would be if they had been Untreated. The maximum pre-divergence deviation is 1.69 and is shown by the black vertical line around 1925. In the right panel, the y -axis is the average treatment effect on the treated (ATT), with a black-dotted horizontal line plotted for zero effect. The upper and lower bounds on the ATT for each post-1950 time are plotted as dashed-yellow and solid-green lines, resp.

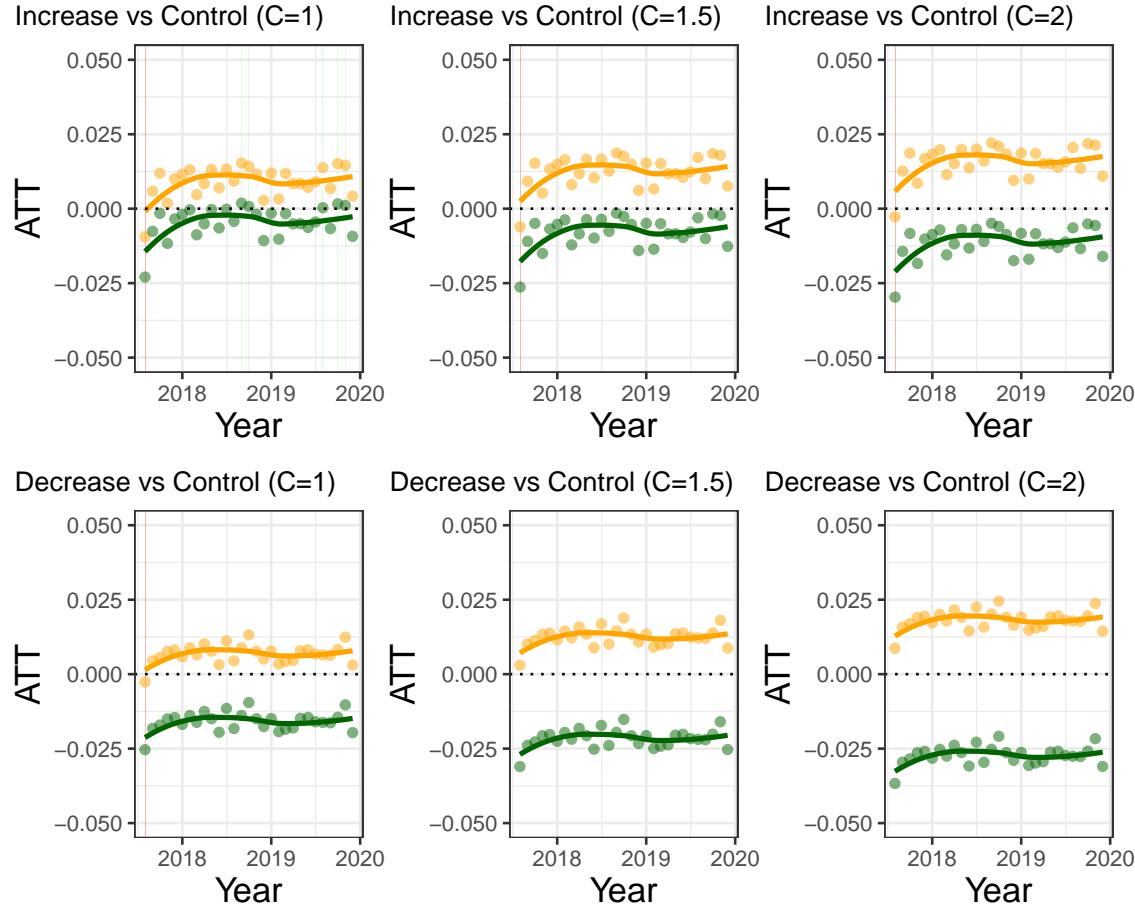
Bounded Deviation Identification (Fixed C=1.0)



Appendix Figure E1. Partial Identification in the Bounded Deviations Approach
Note: The figure is reproduced from Estes & Clark (2025).

The upper and lower bounds implied by this exercise for three different C values are shown in [Figure E2](#). The top row shows estimated ATT bounds comparing the Increase-Treated and Control units, whereas the bottom row shows estimated ATT bounds comparing the Decrease-Treated and Control units.

Comparing Treated Cohorts with Control Upper and Lower Bounds post-Aug 2017



Appendix Figure E2. Relaxing Parallel Trends: Bounded Deviations

Note: The upper (yellow) and lower (green) bounds on the ATT in each post-divergence time are shown from Aug. 2017–Dec. 2020. The points show estimates in each time period, and the solid lines are smoothed fits of those point estimates. The maximum absolute deviations in the pre-divergence period are approximately 0.00674 (Increase vs Control) and 0.0114 (Decrease vs Control).