Legal Aid in the Eviction Context

Pre-Analysis Plan

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Abstract

This project analyzes the comprehensive impact of pro bono legal aid representation in eviction cases. Partnering with the Oklahoma Policy Institute and Legal Aid Services of Oklahoma, we study a randomized intervention offering free counsel to residents facing eviction in two high-eviction-rate ZIP codes in Tulsa. Using difference-in-differences and synthetic control methods, we examine outcomes at the case, individual, and ZIP-code levels — including court outcomes, criminal legal contact, and neighborhood-level housing market dynamics. By analyzing a broader range of downstream effects and using data from a mid-sized city, this study contributes new evidence to debates on eviction prevention and the role of legal aid.

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1 Purpose of Pre-Analysis Plan

Recent policy discussions and literature suggest that legal protections for tenants, while potentially reducing displacement, may exacerbate housing supply constraints.[1] This dynamic raises important questions about whether such interventions shift burdens across individuals rather than resolving underlying scarcity. Our study helps clarify whether providing legal aid delays displacement, alters market dynamics, or enables more stable negotiation outcomes without exacerbating long-term affordability issues.

2 Project Context & Objectives

2.1 Evictions and Land Use

Every year, nearly 2.7 million households face the threat of eviction.[2] Eviction is both a symptom and a cause of economic instability. Individuals who are evicted often come from low-income communities with limited access to services and support, and they often face cascading consequences: worsened physical and mental health,[3] displacement to high-crime neighborhoods,[4] homelessness,[5] damaged credit,[6] and food insecurity.[7] These harms fall disproportionately on historically marginalized populations.[8] While often framed as an urban issue, eviction is a widespread phenomenon across a range of geographies and population densities.[9]

Eviction sits at the intersection of housing affordability, supply constraints, and land use policy. A growing body of empirical research suggests that inelastic housing supply contributes to wealth inequality,[10] environmental harms,[11] and gentrification.[12] Estimates suggest that relaxing land use restrictions in the seven largest U.S. cities could increase national economic output by nearly 8% — a shift equivalent to turning the least productive states into economies as productive as California.[13]

This project situates eviction defense within this broader policy context. Legal aid interventions may help tenants avoid displacement and stabilize housing outcomes. Yet, in a constrained housing market, such protections could—at least in theory—intensify com-

[1] See, *e.g.*, Diamond et al. (2019).

[2] Gromis et al. (2022)

[3] Desmond (2012)

[4] Desmond and Shollenberger (2015)

[5] Collinson and Reed (2018); Burt (2001); Phinney et al. (2007)

[6] Humphries et al. (2019)

[7] King (2018)

[8] Hepburn et al. (2020); Wilson et al. (2021)

[9] Gromis et al. (2022)

[10] Ahern and Giacoletti (2022); Diamond et al. (2019); Glaeser and Gyourko (2018)

[11] Glaeser and Gyourko (2018)

[12] Diamond et al. (2019)

[13] Duranton and Puga (2023)

petition for limited rental units and exacerbate affordability pressures. Conversely, legal assistance may facilitate negotiated outcomes (*e.g.*, extended move-out periods, rental assistance) that reduce harm without worsening supply constraints. Understanding how these dynamics interact is critical to designing eviction interventions that are both effective and economically sustainable.

2.2 Legal Representation and Evictions

This study examines the impact of free legal representation for tenants facing eviction in Tulsa, Oklahoma. While the connection between legal aid and improved outcomes may seem intuitive, researchers have argued that "[t]he access-to-justice crisis is bigger than law and lawyers."[14] Nonetheless, legal counsel remains a promising but understudied tool for preventing eviction and reducing its collateral consequences. Most existing research focuses on high-cost housing markets and examines a narrow set of outcomes.[15] This project seeks to expand that evidence base by studying a broader set of effects in a more generalizable setting.

To that end, we partnered with the Oklahoma Policy Institute (OPI) and Legal Aid Services of Oklahoma (LASO) to evaluate Tulsa's Right to Counsel (RTC) program. Beginning in September 2022, LASO began offering free legal representation to tenants in two ZIP codes (74136 and 74105) with high eviction rates. Two demographically and economically similar ZIP codes (74133 and 74145) did not initially receive the intervention and serve as comparison areas. In April 2024, the RTC program expanded citywide. Our analysis is limited to the 19-month period between September 2022 and April 2024, when only the two treatment ZIP codes were eligible for legal aid.

Tulsa presents a unique opportunity for policy evaluation. It has the 11th highest eviction rate among U.S. cities, with over 14,000 filings per year, half of which result in eviction.[16] Unlike most existing studies of legal aid, which focus on New York or California, our analysis examines a mid-sized city with different institutional and market characteristics.

In addition to direct effects on court outcomes, we assess whether legal aid produces downstream impacts, such as changes in criminal legal system contact or shifts in neighborhood-level housing patterns. The next section describes our data sources, key outcomes, and identification strategy in greater detail.

[14] Sandefur (2019); see also Rostain (2019); Wallat (2019)

[15] Cassidy and Currie (2023); Phillips and Sullivan (2023); Poppe and Rachlinski (2015)

[16] *Top Evicting Large Cities in the United States*, Eviction Lab (using 2016 data), available at https://evictionlab.org/rankings/#/evictions?r=United%20States&a=0&d=evictionRate

3 Data, Methods, and Statistics

3.1 Data

Our analysis examines the impact of Tulsa's Right to Counsel (RTC) program using data from multiple administrative and public sources. We obtain eviction case records from Open Justice Oklahoma (OJO) and the Oklahoma State Court Network (OSCN). These data, compiled by our partners at the Oklahoma Policy Institute (OPI), contain information on litigants, filing dates, hearing outcomes, and judgment details.

From these records, we derive several key outcomes, including whether a tenant appeared in court, whether a judgment under advisement (JUA) was issued, whether a case went to trial, if and when an eviction was ordered, and the number of days a tenant was allowed to remain before vacating. A judgment is coded as favorable to the tenant if the case results in a dismissal, a JUA without a subsequent adverse ruling, or a decision in the tenant's favor.

At the ZIP-code level, we use publicly available data from the U.S. Census Bureau to measure housing development and economic indicators. We focus on new building permits as a proxy for housing supply, alongside indicators such as median household income, rent-to-income ratios, rental occupancy rates, homeownership rates, and unemployment and poverty levels. These contextual variables allow us to examine whether the RTC program coincided with or affected changes in housing availability and affordability.

In addition, because individual names are included in the docket records, we are in theory able to identify repeat eviction filings involving the same tenants or landlords. A challenge with this approach is that our primary datasets do not include date of birth, which is typically required to create accurate longitudinal records, and filter out duplicate and confounding observations.

Ideally, we will be able to match our current data using name and address information with other datasets that also include date of birth. This should in theory allow us to back out dates of birth for individuals in our sample. Proprietary data from vendors such as Verisk (formerly Infutor) or Endato might be useful for this purpose. We will report results of this analysis if we are able to successfully conduct this match.

In addition, if we are able to successfully match in dates of birth, we can assess further downstream consequences beyond housing. This would be by integrated additional data on arrests, charges, and convictions from OJO and OSCN. These criminal legal system records enable us to track whether eviction-related instability correlates with future legal system contact. Eviction can increase vulnerability to criminal exposure by contributing to homelessness or other forms of instability. By linking court and criminal records, we examine whether tenants who received legal aid differ systematically from those who did not in their subsequent involvement with the legal system.

3.2 Key Performance Indicators

Our outcome measures are organized by level of analysis: case, individual, and ZIP code. Key performance indicators (KPIs) are presented in Tables 1, 2, and 3.

Table 1: **Key Performance Indicators - Case Level**

Outcome	Topic	Measure	Source
Case			
Appearance	Housing	Binary	LASO, OJO, OSCN
Judgment Under Advisement[a]	Housing	Binary	LASO, OJO, OSCN
Dismissal	Housing	Binary	LASO, OJO, OSCN
Trial	Housing	Binary	LASO, OJO, OSCN
Tenant Favorable Outcome[b]	Housing	Binary	LASO, OJO, OSCN
Time to Execution	Housing	Numeric	LASO, OJO, OSCN

[a] Judgment for plaintiff or a default judgment.

[a] Indicates whether the final outcome was a dismissal or JUA.

Table 2: **Key Performance Indicators - ZIP Code Level**

Outcome	Topic	Measure	Source
Supply Side			
Change in # of New Building Permits	Housing	Numeric	OJO, OSCN, US Census Bureau
Change in Housing Value	Housing	Numeric	OJO, OSCN, Infutor
Demand Side			
Change in Eviction Rates	Housing	Numeric	OJO, OSCN

Table 3: **Key Performance Indicators - Individual Level**

Outcome	Topic	Measure	Source
Subsequent Cases (within 1 year)			
Subsequent Eviction Filing	Housing	Binary	LASO, OJO, OSCN
Misdemeanor Prosecution	Crime	Numeric	OSCN, OK Dept. of Corr., Tulsa County IIC
Appearance in Small Claims Court	Legal	Numeric	OSCN, OK Dept. of Corr., Tulsa County IIC
Felony Prosecution	Crime	Numeric	OSCN, OK Dept. of Corr., Tulsa County IIC

Note: These outcomes will be reported only if we are able to use supplemental data to create longitudinal datasets by matching in dates of birth for individuals in our sample, as described earlier.

3.3 Intervention Design

3.3.1 Timeline

The intervention began in September 2022 and concluded in March 2024. During this period, Legal Aid Services of Oklahoma (LASO) offered free legal representation to all tenants facing eviction in ZIP codes 74105 and 74136. These ZIP codes were selected due to high eviction rates and socioeconomic characteristics. Two similar ZIP codes (74133 and 74145) were not initially covered by the intervention and serve as comparison areas.

Importantly, even though the study period has ended, we have not yet accessed the underlying data. Accordingly, this remains a "pre-analysis plan" in which we currently describe our methods of analysis and outcomes we will report without knowing the results of any analysis.

3.4 Statistical Analysis

3.4.1 Case-Level Outcomes

We estimate the effect of the RTC program on eviction case outcomes using a difference-in-differences framework. Our unit of analysis is the individual eviction case, and treatment status is assigned at the ZIP-code level. We compare outcomes before and after the start of the program in treated versus control ZIP codes. Because tenants in treated areas became eligible for legal aid beginning in September 2022, our post-treatment indicator reflects case filings after that date.

To isolate the effect of initial exposure, we limit the sample to each tenant's first observed eviction case during the study period. If a second eviction is filed for the same tenant within one year, we exclude them from the sample to avoid contamination of post-treatment effects.

The primary estimating equation is:

$$Y_{izt} = \alpha + \beta \cdot (\text{Treated}_z \times \text{Post}_t) + X_{zt} + \gamma_t + \epsilon_{izt} \tag{1}$$

where Y_{izt} is the case-level outcome for tenant i in ZIP code z and time t; Treated_z is a binary indicator for treatment ZIPs; Post_t is an indicator for the post-intervention period; X_{zt} is a set of time varying ZIP-code specific variables; and γ_t denotes time fixed effects. Standard errors are clustered at the ZIP-code level.

3.4.2 ZIP-Code-Level Outcomes

To examine aggregate effects, we analyze ZIP-code-level outcomes such as eviction filing rates, housing values, and new building permits. These outcomes are available for a wider range of ZIP codes, enabling more robust comparison.

We use the following difference-in-differences specification:

$$Y_{zt} = \alpha + \beta \cdot (\text{Treated}_z \times \text{Post}t) + X_{zt} + \theta_z + \gamma_t + \epsilon_{zt} \tag{2}$$

where θ_z and γ_t represent ZIP and time fixed effects. Standard errors are clustered at the ZIP-code level.

Because ZIP-level treatment assignment was not randomized across the full citywide sample, the DiD estimates should be interpreted as quasi-experimental. We assess pre-treatment comparability via visual inspection and placebo tests.

3.4.3 Individual-Level Outcomes

If we can merge in dates of birth and create accurate longitudinal datsets (see section 3.1), we will also analyze longer-run individual-level outcomes, including involvement in the criminal legal system and other downstream indicators. The unit of analysis here is the individual tenant. Our analysis includes only those with a single eviction case during the study window, excluding those with subsequent filings within one year. This restriction ensures clean measurement of one-year follow-up outcomes.

We use the same difference-in-differences approach, estimating:

$$Y_{jzt} = \alpha + \beta \cdot (\text{Treated}z \times \text{Post}_t) + X_{zt} + \gamma_t + \epsilon_{jzt} \tag{3}$$

where Y_{jzt} is the outcome for individual j in ZIP code z and time t. Standard errors are clustered by ZIP code.

3.4.4 Synthetic Control Methods

For selected ZIP-code-level outcomes, we use synthetic control methods to construct a more finely tuned counterfactual. We identify a weighted combination of comparison ZIP codes that closely match the treated ZIPs in pre-intervention characteristics and trends.

This approach allows for outcome-specific inferences that do not rely on the parallel trends assumption. We apply this method to outcomes such as building permits and assessed property values using data from OJO, OSCN, and the U.S. Census Bureau.

4 Limitations

While this study is designed to produce credible evidence on the impact of legal aid in eviction cases, several limitations should be noted.

Limited Number of Clusters

The Right to Counsel intervention was randomized at the ZIP-code level, but only two ZIP codes were assigned to treatment and two to control. This small number of treated clusters limits our ability to fully leverage the benefits of randomization and restricts the use of conventional RCT inference. As a result, we rely on difference-in-differences and synthetic control methods to estimate causal effects. These methods help mitigate the risk of imbalance and improve statistical power but depend on additional assumptions, such as parallel trends or good pre-treatment fit, which must be validated empirically.

Parallel Trends Assumption

Our difference-in-differences analyses assume that, in the absence of the intervention, treated and control ZIP codes would have followed similar trends in outcomes. While we conduct pre-treatment visual inspections and placebo tests to assess this assumption, it cannot be tested directly and remains a potential threat to validity.

Generalizability

The intervention was implemented in a single mid-sized city, with ZIP codes selected based on high eviction rates. While Tulsa is arguably more representative of the average U.S. city than New York or San Francisco, caution should still be exercised in generalizing results to other geographies or policy environments.

Unit of Assignment vs. Unit of Analysis

Treatment was assigned at the ZIP-code level, but outcomes are measured at the case and individual levels. Although we account for clustering in our standard errors, the effective sample size for treatment inference remains constrained by the number of independent clusters. In addition, all individuals within a ZIP code receive the same treatment status, which limits our ability to distinguish between neighborhood effects and individual treatment effects.

Data Limitations and Measurement Error

Our analyses rely on administrative data from court records, housing filings, and public criminal justice sources. These data may contain entry errors, missing fields, or timing mismatches across systems. Moreover, some outcomes — particularly criminal legal involvement — may be underreported if individuals move out of jurisdiction or interact with systems not captured by our data sources.

Sample Restrictions

To ensure consistency in follow-up and avoid contamination from overlapping exposures, we restrict our analysis to each individual's first observed eviction case and exclude individuals with a second filing within one year. While this strengthens our ability to attribute downstream outcomes to a single intervention, it may also limit our ability to assess repeat filings or cumulative treatment effects.

Potential Spillovers

We do not explicitly model spillovers between ZIP codes. It is possible that the intervention affected landlord behavior across ZIP boundaries, or that tenants moved between treated and control areas. If such spillovers occurred, our estimates may be biased toward zero, and our interpretation of direct treatment effects may be conservative.

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