UDS Displaced Voices

Using Data Science Tools for Housing Justice

Project Objectives

- **Primary Goal:** Forecast eviction numbers for 2025 to enable proactive budgeting
- **Target:** Assist Arizona government in allocating rental assistance funds efficiently
- **Approach:** Three-pronged analysis using 2022-2024 eviction data
- **Impact:** Ensure no household is left behind due to funding shortfalls

Track Members

- **Visualization Track**

  Members: Nhi Nguyen, Devang Singhal

- **Statistical analysis Track**

  Members: Sean Skinner, Leticia Favero Lopes

- **Predictive Modeling Track**

  Members: Sai Roy, Harshini Balamurugan Vadivazhagi,

  Rati Tabatadze, Poojitha Nuthalapati, Tylor Vongsenekeo

How each track helps with the project

1

Visualization Analysis - Exploratory data insights through visual patterns

2

Statistical Analysis - Identifying key drivers of eviction risk
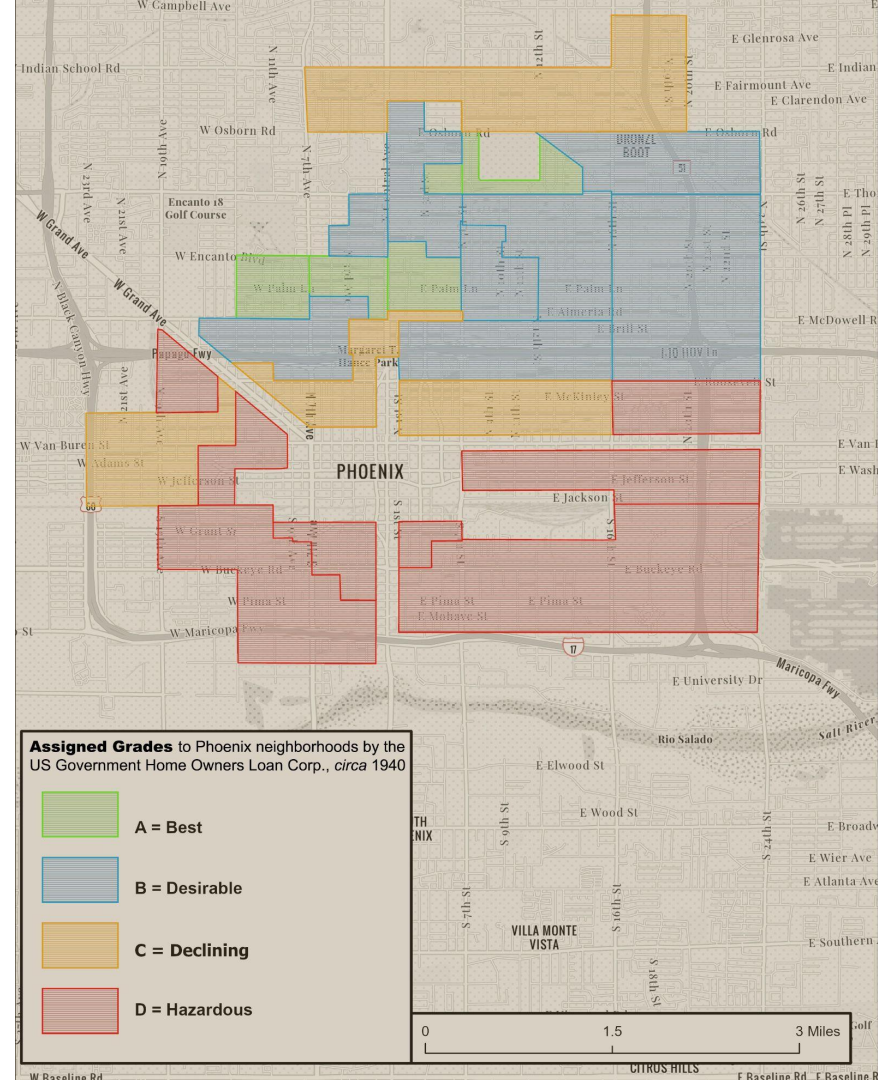
3

Predictive Modeling - Time series forecasting for 2025

Historical Context(redlining)

In 1932 the Home Owners' Loan Corporation was created to buy foreclosed properties and delinquent mortgages, to then refinance them under people who could pay them- extending the life of housing loans. In 1935 the HOLC developed "security maps" that show the riskiness of neighborhoods for lending purposes. The Federal Housing Administration would use this map to determine where loans are granted.

Assigned Grades to Phoenix neighborhoods by the US Government Home Owners Loan Corp., *circa* 1940

- **A = Best**
- **B = Desirable**
- **C = Declining**
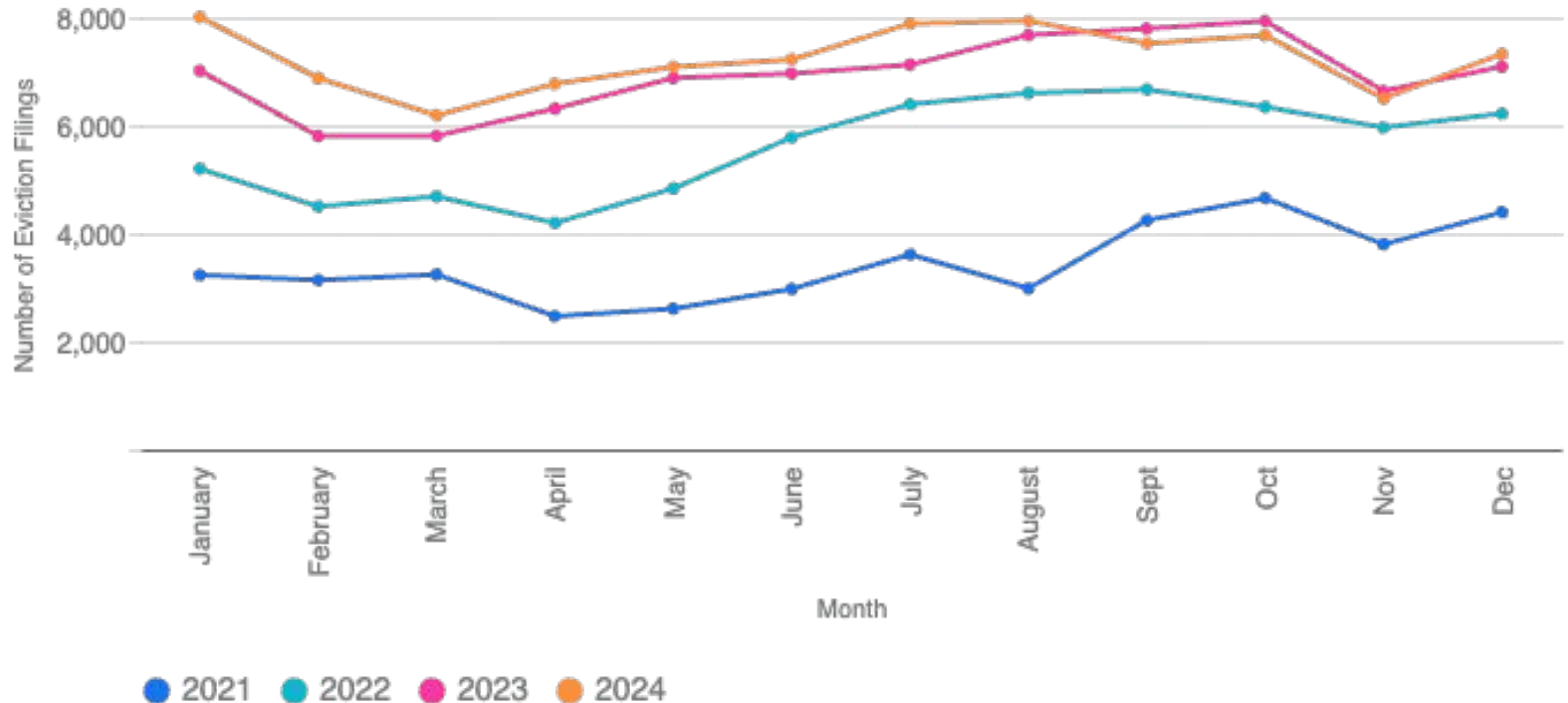- **D = Hazardous**

Visualization track

Nhi Nguyen, Devang Singhal

Eviction Filings (2021 - 2024)

Monthly Eviction Filings by Year (2021-2024)

The Cases With Data and Sealed Cases

THE MISSING CROWD

Each figure = ~871 eviction cases | 34% are sealed with unknown outcomes
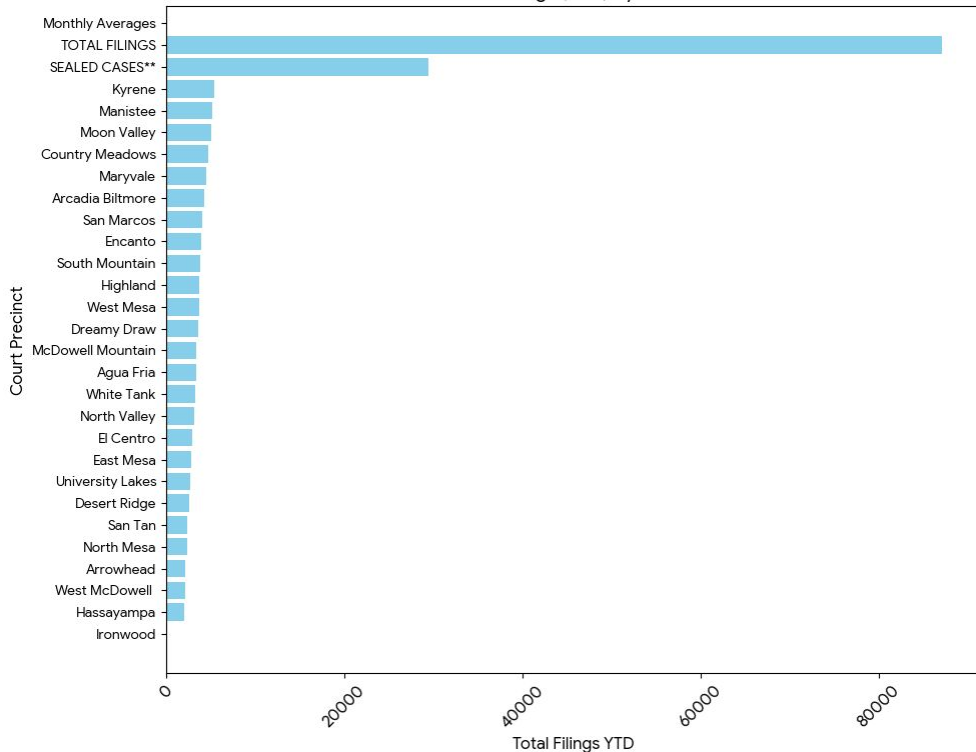
66 = Cases with Data (57,704)   34 = Sealed Cases (29,426)

Maricopa County Evictions 2024

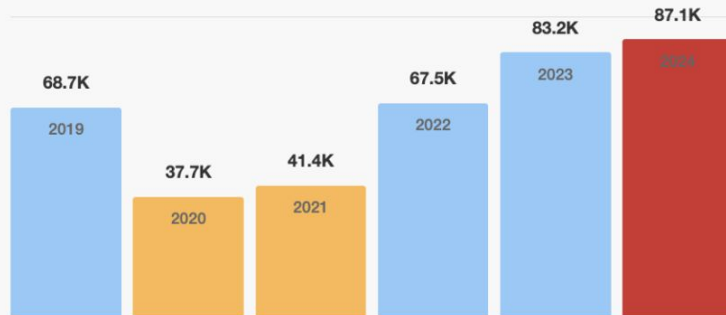2024 Eviction Filings (YTD) by Court Precinct

Courts process: Legal representation and Cases filed

THE JUSTICE GAP (CORRECTED)
Legal Representation in Maricopa County Evictions
57,704 cases with data (excludes 29,426 sealed cases)

Landlords with Lawyers: 54,367 (94.2%)

Tenants with Lawyers: 90 (0.2%)

Number of Cases
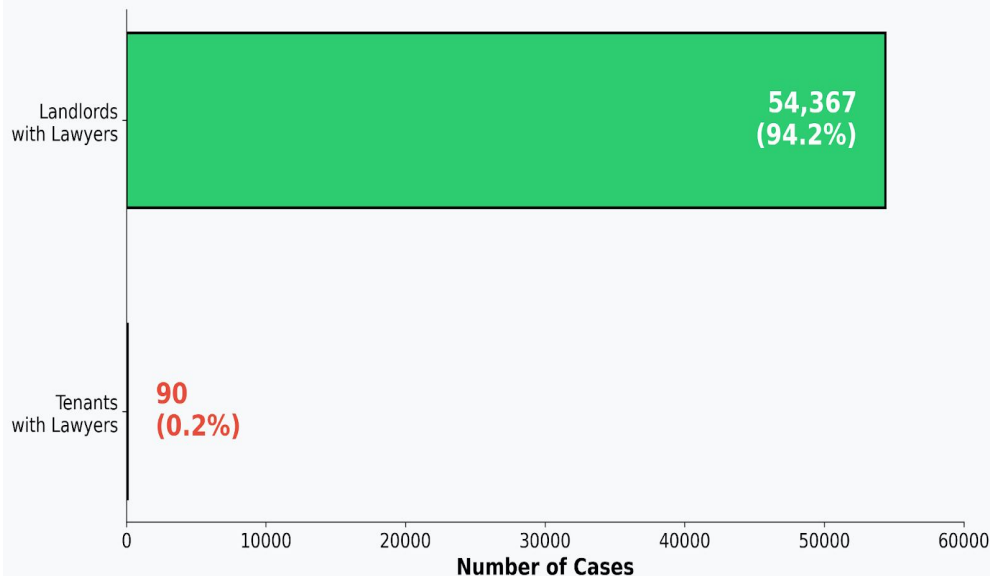
87,130

Total eviction cases filed in 2024

2019: 68.7K
2020: 37.7K
2021: 41.4K
2022: 67.5K
2023: 83.2K
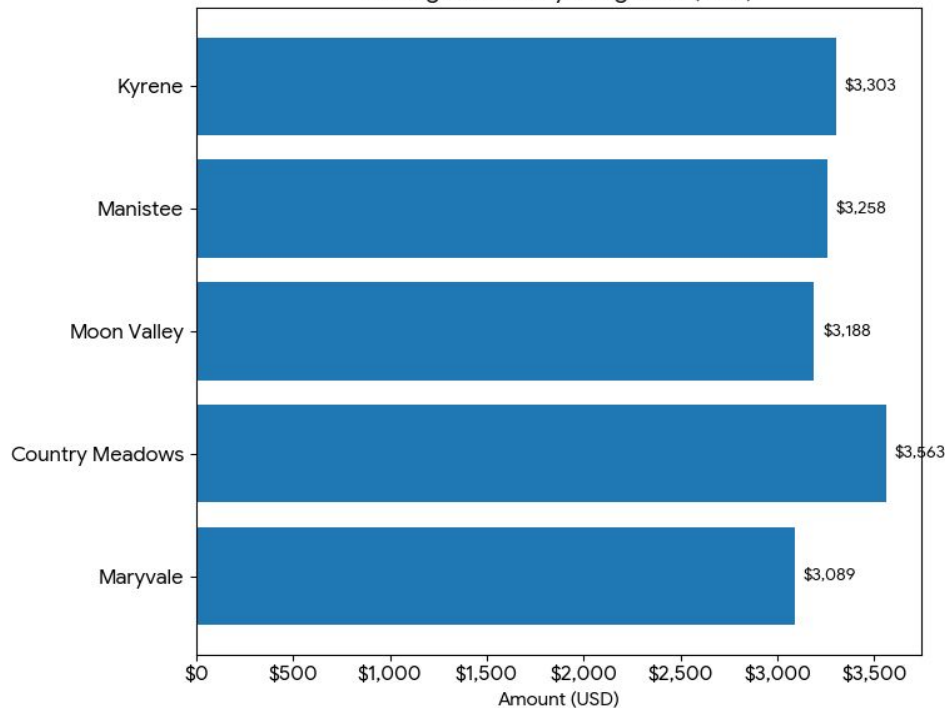2024: 87.1K

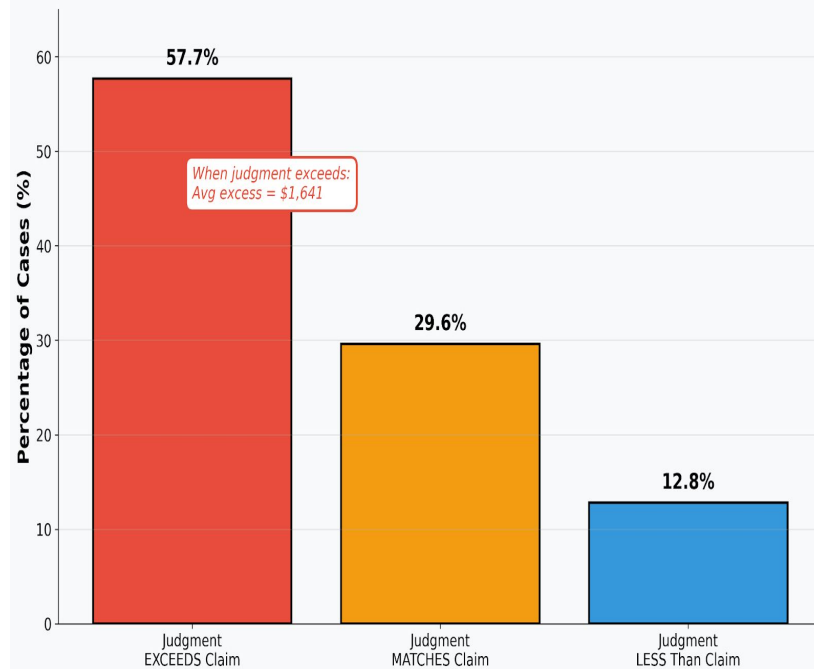238 Cases filed per day

10 Cases filed per hour

1 Case every 6 minutes

Judgement inflation crisis
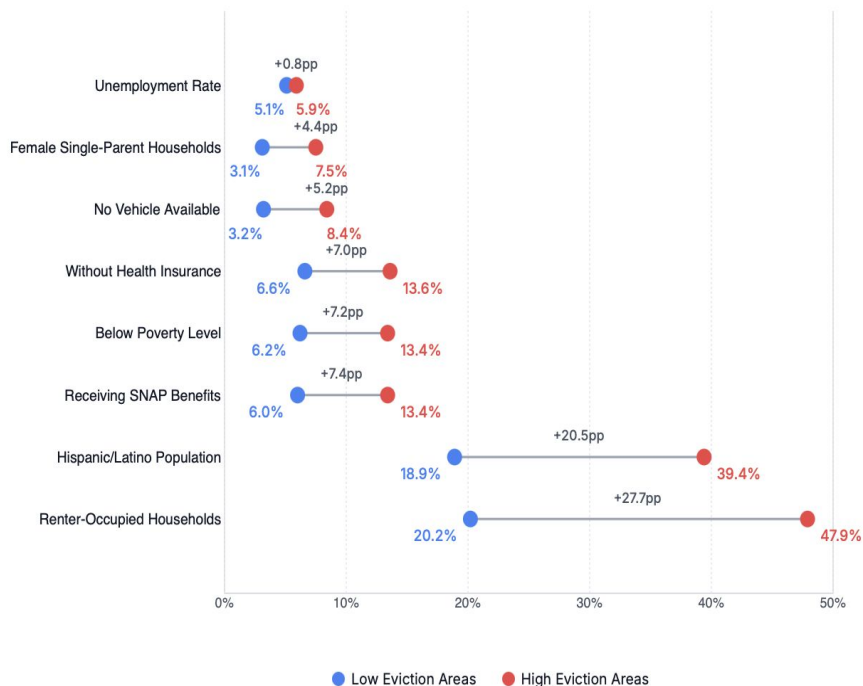

Average Monetary Judgment (USD)

JUDGMENT INFLATION CRISIS
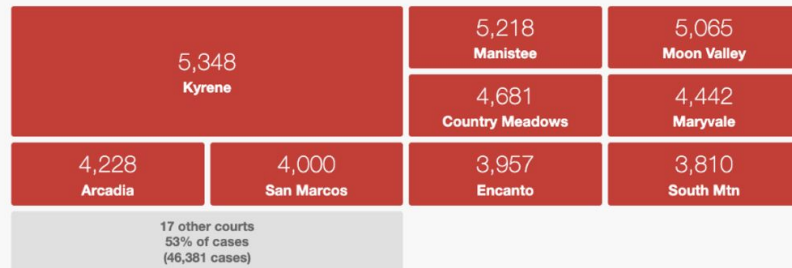How Judgments Compare to Claims

Demographics of the tenants

Demographic Disparity in Eviction Tracts
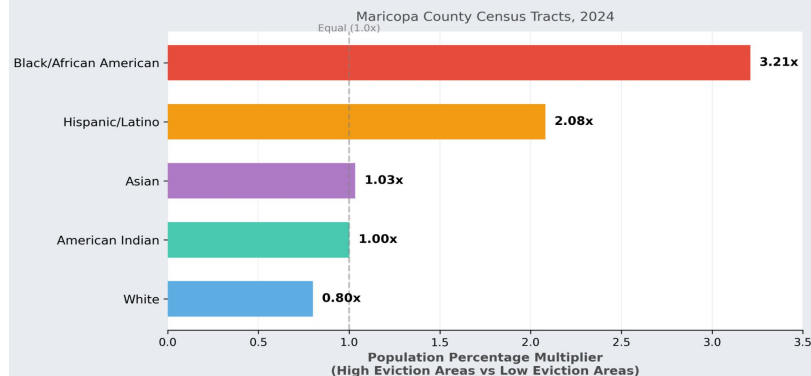### Comparing Metrics in Low vs. High Eviction Areas

- Unemployment Rate — +0.8pp — 5.1% (Low) / 5.9% (High)
- Female Single-Parent Households — +4.4pp — 3.1% (Low) / 7.5% (High)
- No Vehicle Available — +5.2pp — 3.2% (Low) / 8.4% (High)
- Without Health Insurance — +7.0pp — 6.6% (Low) / 13.6% (High)
- Below Poverty Level — +7.2pp — 6.2% (Low) / 13.4% (High)
- Receiving SNAP Benefits — +7.4pp — 6.0% (Low) / 13.4% (High)
- Hispanic/Latino Population — +20.5pp — 18.9% (Low) / 39.4% (High)
- Renter-Occupied Households — +27.7pp — 20.2% (Low) / 47.9% (High)

● Low Eviction Areas ● High Eviction Areas

9 COURTS HANDLE 47% OF ALL CASES

5,348 Kyrene	5,218 Manistee	5,065 Moon Valley
	4,681 Country Meadows	4,442 Maryvale
4,228 Arcadia	4,000 San Marcos	3,957 Encanto / 3,810 South Mtn

17 other courts
53% of cases
(46,381 cases)

40,749 cases in just 9 courts — extreme volume creates assembly-line justice

Racial Eviction Disparity Index
Maricopa County Census Tracts, 2024

Equal (1.0x)

- Black/African American — **3.21x**
- Hispanic/Latino — **2.08x**
- Asian — **1.03x**
- American Indian — **1.00x**
- White — **0.80x**
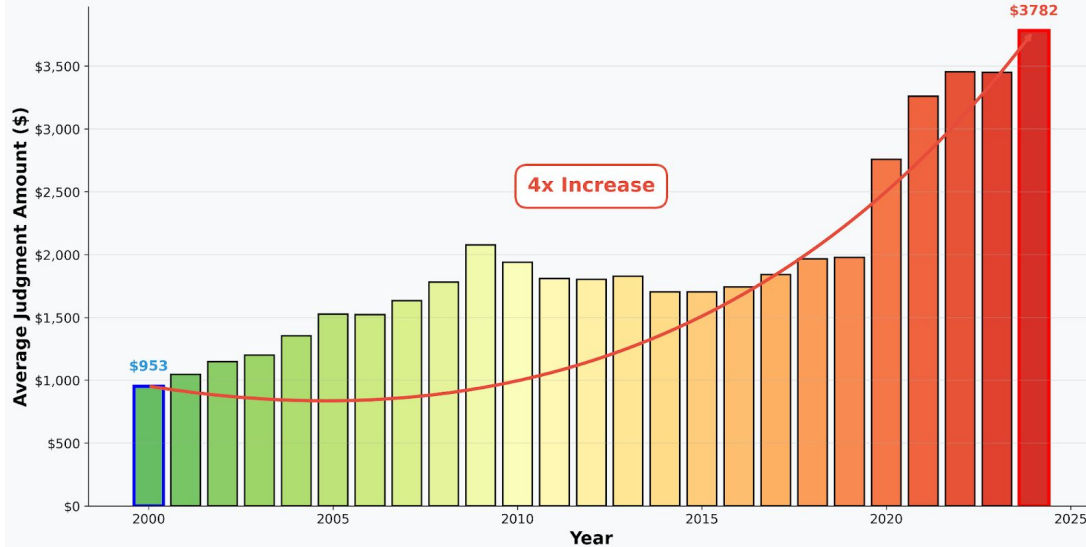
Population Percentage Multiplier
(High Eviction Areas vs Low Eviction Areas)

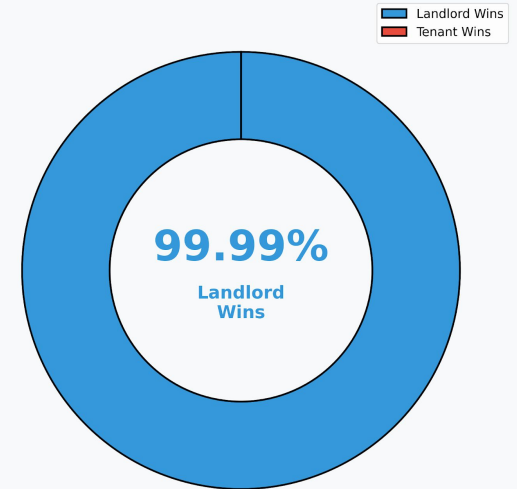*High eviction areas have 3.21x more Black population and 2.08x more Hispanic/Latino population than low eviction areas*

The outcome and monetary burden of eviction cases

THE RISING BURDEN
Average Eviction Judgment Over Time

$3782

4x Increase

$953

THE OUTCOME
Eviction Case Judgments (2024)

Landlord Wins
Tenant Wins

99.99%
Landlord Wins

Statistical Analysis track

Sean Skinner, Leticia Favero Lopes

Initial Factors

- **Dependent Variable**: Eviction Rate
- **Independent Variables**: Income and
- **Ethnic Demographics**:
  - Median Income, Median Monthly Cost, Median Gross Rent
  - Racial Percentages
  - Single Male Parent, Single Female Parent, Disability, Below Poverty Line Percentages

First Steps

- Cleaned data to account for missing values
- Removed outlier
  - One region had an eviction rate over ten times the next highest (ZIP code 85008, near Papago Park)
- Generated linear regression, analyzed multicollinearity

Iterative Regression

- Removed ethnic demographic variables due to high levels of multicollinearity
- Performed log transformations on dependent and some independent variables for goodness-of-fit
- Iterated through until best fit found

Final Regression

- Most Statistically Significant Term Highlighted
- Interpretation: an increase of 1 percentage point in single female parent households corresponds to an increase in the eviction rate by a factor of approximately 5%

```
Call:
lm(formula = log_eviction_rate ~ log_income + log_rent + pct.below.poverty.level +
    pct.female.single.parent.household + pct.male.single.parent.household +
    pct.not.us.citizen + median.monthly.housing.cost, data = df_no_outlier)

Residuals:
    Min      1Q  Median      3Q     Max
-4.3506 -0.4343  0.3441  0.9399  3.3981

Coefficients:
                                      Estimate Std. Error t value Pr(>|t|)
(Intercept)                         -2.6193841  2.2755093  -1.151  0.24995
log_income                          -0.1397206  0.2347481  -0.595  0.55185
log_rent                             0.1232324  0.2343360   0.526  0.59909
pct.below.poverty.level              0.0087954  0.0076537   1.149  0.25076
pct.female.single.parent.household   0.0485507  0.0111563   4.352 1.49e-05 ***
pct.male.single.parent.household     0.0290288  0.0254186   1.142  0.25371
pct.not.us.citizen                  -0.0082124  0.0026073  -3.150  0.00168 **
median.monthly.housing.cost         -0.0010254  0.0004869  -2.106  0.03546 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.475 on 1013 degrees of freedom
  (48 observations deleted due to missingness)
Multiple R-squared:  0.09702,   Adjusted R-squared:  0.09078
F-statistic: 15.55 on 7 and 1013 DF,  p-value: < 2.2e-16
```
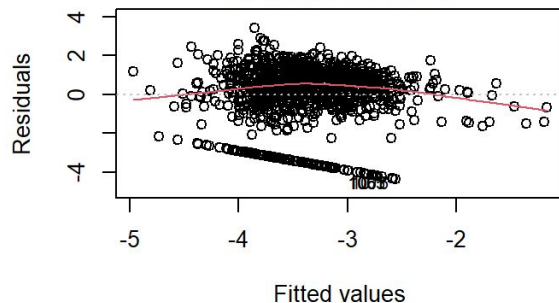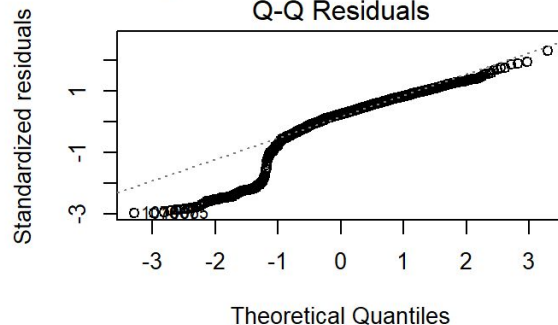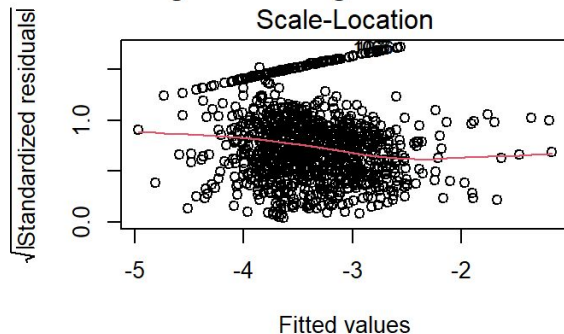
Diagnostics
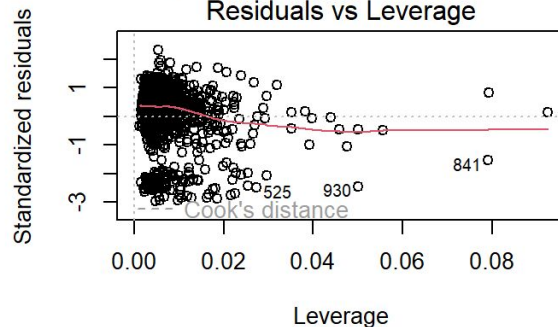
Predictive Modeling

Sai Roy, Sudamshu Rao, Harshini Balamurugan Vadivazhagi, Rati Tabatadze, Poojitha Nuthalapati, Tylor Vongsenekeo

Our Prediction Strategy

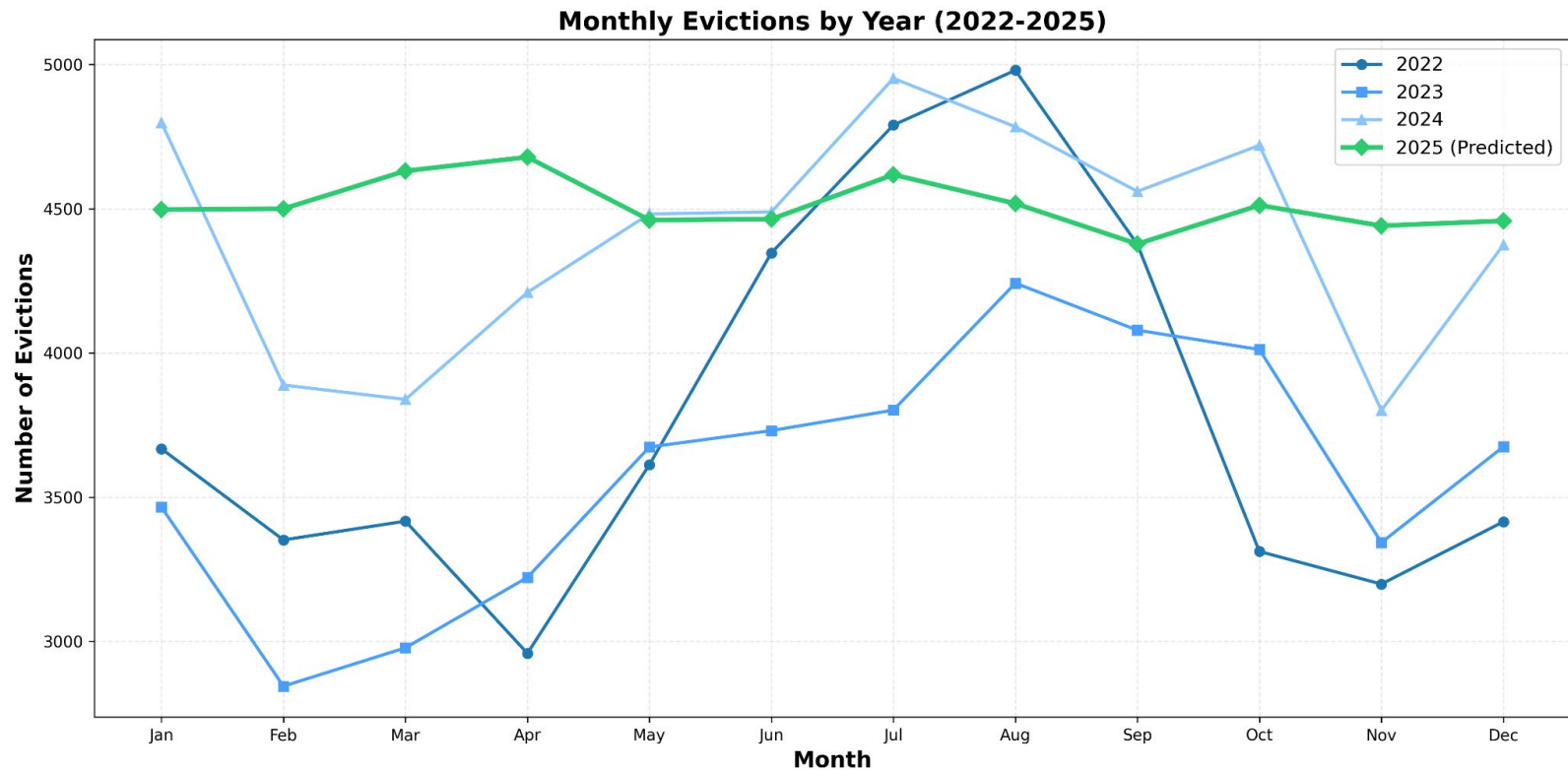**The Method:** Learning from the past to predict the future

The Data: Three years of Maricopa County eviction records (2022-2024)

The Goal: Forecast monthly evictions throughout 2025

The Benefit: Helps Arizona plan and budget before families are in crisis

Time Series Graph

Monthly Evictions by Year (2022-2025)

Dataset

Using sealed records from 2022–2024 to predict eviction rates for 2025.

Year	Total Records	Average per Month
2022	45,428	3,785
2023	43,069	3,589
2024	52,900	4,408
2025 (Predicted)	**54,143**	**4,513**

What the data says

Key Takeaways:

- **16% increase** from 2022 to 2024 - trend continues into 2025
- **Summer months (July-August)** consistently highest risk across all years
- **2025 prediction: 54,143 evictions** - highest year yet
- **Monthly average rising:** From 3,785 (2022) to 4,513 (2025)
- **Intervention window:** Spring months show early warning signs before summer peaks

Compare with the 2025 actual evictions data

Current Statistics

Month	Evictions
January	7,613
February	7,070
March	5,996
April	6,788
May	7,101
June	7,029
July	7,250
August	7,565
September	7,310

Month	Prediction
January	4,497
February	4,500
March	4,631
April	4,679
May	4,461
June	4,464
July	4,618
August	4,518
September	4,378

Prediction Results

Moving Forward

Current Limitations:

- **Data Scope:** Analysis limited to unsealed eviction records; sealed cases not captured in dataset
- **Variable Coverage:** Model focuses on temporal patterns; additional socioeconomic factors could enhance accuracy
- **Geographic Granularity:** County level analysis; census tract detail would enable targeted interventions

Future Enhancements:

- **Expanded Data Integration:** Incorporate datasets like the labor statistics and american community survey data
- **Advanced Modeling:** Deploy neural networks to discover complex cross dataset relationships

Conclusion
UDS Displaced Voices

" These predictions aren't just numbers, they're real individuals needing support and each statistic represents families, children, and communities we can protect.