Targeting Assistance and Preventing Eviction: Tract-Level Analysis of ERA Distribution and Impact

Working Paper

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Chapter 3. Targeting Assistance and Preventing Eviction: Tract-Level Analysis of ERA Distribution and Impact

Main Findings and Takeaways

- Emergency Rental Assistance (ERA) funds were largely distributed in neighborhoods with the highest eviction risk and neighborhoods with higher shares of Black, Asian, and unemployed residents, as well as higher shares of renters.
- Although ERA went to households in neighborhoods with higher eviction risk, funding did not always match the level of need—neighborhoods at the 75th percentile and higher of eviction risk and with high shares of Black residents, unemployed people, and renters did not receive proportionally as much ERA.
- Overall, neighborhoods in which higher amounts of total ERA funding was distributed saw fewer eviction filings during the pandemic, compared to neighborhoods that received less ERA funding. The effect of ERA was stronger in neighborhoods with more unemployment and rent burden.

Data and Methods

This chapter shifts from the previous county-level analyses to examine ERA distribution and its impact on evictions at the neighborhood (census tract) level. This level of detail allows for a much more localized evaluation of ERA's impact on housing instability and focuses on two main questions:

1. Did ERA reach the neighborhoods most at risk of eviction?
2. Did ERA reduce eviction filings, and in which neighborhoods was this effect greatest?

To address these questions, this study uses multilevel modeling (MLM) and two neighborhood-level datasets, integrating ERA payment data, eviction risk metrics, and census data. States and counties lacking sufficient payment or eviction data were excluded to ensure data quality. We have two analytical approaches:

- **Analysis 1: Emergency Rental Assistance:** Assesses whether ERA payments reached neighborhoods in need, using the total ERA dollars distributed to each tract as the outcome variable.

- **Analysis 2: Prevented Eviction Filings:** Examines the impact of ERA on eviction filings, using the Eviction Prevention Ratio (EPR) from the previous chapter—the change in eviction filings during the pandemic compared to pre-pandemic levels, normalized by renter population—as the outcome.

Explanatory variables include demographic data from the 2018-2022 5-year American Community Survey, ERA payment records from HUD and the Treasury, eviction filings from the Legal Services Corporation (2023) and Eviction Research Network (2025), and eviction and displacement risk estimates from the Urban Displacement Project's Housing Precarity Risk Model (HPRM) (2025).

Analysis 1 covers a larger share of U.S. neighborhoods, including 48,069 census tracts across 39 states and D.C., while Analysis 2 covers a smaller share, with 11,988 neighborhoods across 10 states. The difference in scale is due to the limited availability of reliable eviction filing data. Analysis 2's Eviction Prevention Ratio (EPR) relies on observed eviction filings with address-level information that can be aggregated to the census tract level, data which is only available in 10 states. In contrast, Analysis 1 focuses on ERA distribution and utilizes the novel HPRM to provide eviction risk estimates in areas where filing data is unavailable. This approach allows Analysis 1 to leverage a much larger sample size, primarily limited to areas with reliable ERA data availability.

Dependent Variables

Analysis 1: Emergency Rental Assistance Payments

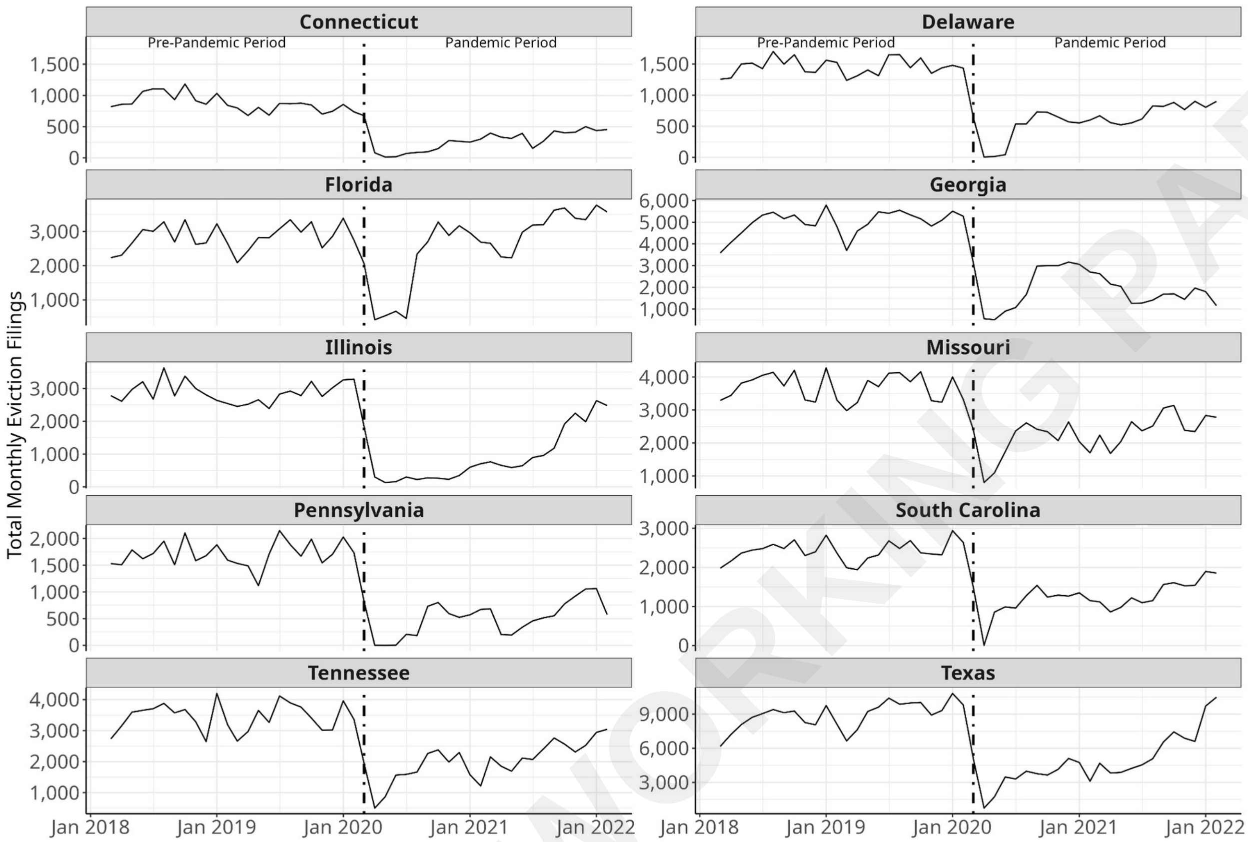
Similar to the county-level model, this model includes total assistance distributed in each neighborhood to help tenants pay rent during the study period. Since this is a spatial analysis, individual payments are not linked to households; instead, ERA dollars are aggregated to addresses within their respective neighborhoods. In both models, the natural logarithm is applied to ERA dollars to induce normality.

Analysis 2: Prevented Eviction Filings

The second model uses a tract-level Eviction Prevention Ratio (EPR)—which is the difference in the study period's **(**March 1, 2020, through February 28, 2022) eviction filings from the previous two year historical average (March 1, 2018 through February 29, 2020), normalized by the tract renter population per 1,000 renters. EPR is calculated similarly as in the previous county-level chapter but is instead normalized by tract renter population (See Appendix A for more details). Records are also winsorized to the bottom 5% to improve model fit without dropping outliers (see Appendix B for more details).

Exhibit 3.1 reports the total monthly eviction filing counts by state. The dashed line indicates the start of the pandemic in March 2020. The y-axis is allowed to vary to better highlight trends within each state. What is most notable is that across states, similar patterns emerge—relatively stable eviction filing rates prior to the pandemic, a steep decline by March 2020, and then either a relatively quick or gradual return toward pre-pandemic levels. In some states, such as Florida and Texas, eviction rates return to or exceed pre-pandemic levels before the end of the study period, whereas many other states do not return to pre-pandemic levels during this time. Notably, some states like Pennsylvania and Georgia experience a second decline in eviction filings during the study period.

Exhibit Targeting Assistance and Preventing Eviction: Tract-Level Analysis of ERA Distribution and Impact.14: Monthly pandemic vs pre-pandemic eviction filing rates by state



Source: Figure based on authors' calculations using eviction data from the Legal Services Corporation.

Explanatory Variables

Analysis 1

There are two key explanatory variables in Analysis 1 predicting ERA funding—displacement risk and eviction risk. These variables come from the Housing Precarity Risk Model (HPRM) (Thomas et al. 2025), which is an advanced analytical tool designed to estimate the risk of low-income residential displacement and eviction at the census tract-level, utilizing annual, national household consumer migration data and eviction filing data (see Appendix B for details on model construction). Displacement risk is associated more with renters with incomes between 50% to 80% of AMI and reflects "soft" displacement—whereby renter households move as a result of rising rents. Eviction risk occurs more often to renter households with very low incomes (less than 50% of AMI) and is linked with forced or involuntary "hard" displacement. While some neighborhoods can experience both displacement and eviction risk, these two measures often do not overlap, providing an important and nuanced understanding of low-income mobility.[21] Given that displacement risk—as measured here—is more likely to be related to neighborhood instability in the form of rising rents and neighborhood change, it is more likely that ERA funding was better targeted to neighborhoods at risk of eviction.[22]

21 For example, San Francisco has low eviction risk but extremely high displacement risk. This is because the city has strong eviction laws and protections that reduce eviction risk. However, low-income tenants are still widely displaced due to extraordinarily high rents in the city.

Analysis 2

The key explanatory variable in Analysis 2, which predicts eviction filings, is the distribution of ERA payments in a neighborhood.[23] For parsimony, ERA is operationalized in the same way as in the previous county chapter and is limited to only measure total dollars of rental assistance distributed by all state and local ERA programs within a neighborhood. More details on the ERA data are available in Appendix A.

Other Independent Variables

The other independent variables for the two models are organized into the same three categories as in the previous county chapter: tenant protections, neighborhood demographics, and housing market context. For consistency with the previous county-level analysis, many of the same variables are used in these analyses and are selected based on findings from prior eviction literature, statistical importance derived from the Housing Precarity Risk Model (HPRM), and overall model fit. Analysis 1 is limited to ten variables that explain ERA distribution, while Analysis 2 includes twelve variables that predict eviction filings. Broadly, they include:

- Tenant protections: Key tenant protections include controls for the impact of state-level notice or filing eviction moratoria during the COVID-19 pandemic; differences in state eviction timelines; and the count of state-level tenant protections like limits on late fees, just-cause requirements, and access to legal counsel.[24]
- Neighborhood demographics: Important neighborhood demographics that could influence ERA and eviction filing rates were also included as controls. This includes measures of racial composition (e.g., share of residents who are Black, Asian, or Hispanic or Latino), a measure of neighborhood diversity (the Theil's Information Index), income inequality (Gini), unemployment, and education.
- Housing market context: Key housing market variables control for varying market conditions and include share of renter-burdened households and the share of renters in a housing market. Initial controls for median rent and vacancy rate were dropped because of concerns of collinearity and parsimony.

Unit of Analysis and Spatial Scope

This study uses census tracts as the unit of analysis in this study, which contain an average of 4,000 people and occur at the same spatial scale as neighborhoods. Census tracts are a relatively small geographic unit that allow reliable estimates and consistently nest within counties and

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22 Displacement risk is quantified as the net migration rate of low-income renter households (those earning less than 80% of AMI); negative values indicate displacement. Eviction risk is measured as an odds ratio relative to the state in which the census tract is located, with values exceeding one signifying a higher-than-average risk of eviction. Due to the limited availability and challenges associated with collecting eviction data, the HPRM incorporates estimates to address data gaps, thereby enabling the analysis of a broader range of areas where ERA was distributed.

23 Since this chapter focuses on neighborhoods instead of counties, ERA dollars are aggregated to the census tract instead of the county.

24 This analysis focuses on state rather than federal moratoria due to better data availability and consistency, measuring the number of days notice or filing moratoria were in effect during the pandemic. It prioritizes these moratoria since they directly precede the main outcome of interest: eviction filings.

states. Given that census tracts are commonly used in urban studies as the best proxies for neighborhoods, this report uses "census tract" and "neighborhood" interchangeably.

Exhibit Targeting Assistance and Preventing Eviction: Tract-Level Analysis of ERA Distribution and Impact.15: Neighborhoods included in each study

	Count of Tracts	Count of Counties	Count of States	Included States
Analysis 1: Emergency Rental Assistance Payments	48,069	1,759	40	Alabama, Arkansas, California, Colorado, Connecticut, Delaware, District of Columbia, Florida, Georgia, Idaho, Illinois, Iowa, Kansas, Kentucky, Louisiana, Maryland, Massachusetts, Michigan, Mississippi, Missouri, Montana, Nebraska, Nevada, New Hampshire, New Jersey, North Carolina, Oklahoma, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, West Virginia, Wisconsin, Wyoming
Analysis 2: Prevented Eviction Filings	11,988	200	10	Connecticut, Delaware, Florida, Georgia, Illinois, Missouri, Pennsylvania, South Carolina, Tennessee, Texas

Exhibit 3.2 lists the tract and county counts for the states in each model. Note the larger coverage in Analysis 1 because of the use of the HPRM, which allows more states without eviction data to be included in the analysis. Analysis 2 is restricted by tracts, counties, and states with overlapping ERA and eviction filing data (see the Appendix for a map of where study tracts are located across the U.S.).

Analytic Strategy: Multilevel Models

The analytic approach in this chapter employs a multilevel modeling (MLM) framework to examine both the distribution of ERA funds and their impact on eviction filing rates. We use because it accounts for the nested structure of the data—neighborhoods (level 1) nest within counties (level 2) which nest within states (level 3). This theory-driven, parametric approach tests specific hypotheses while also allowing the models to separate the effects of neighborhood-level factors from broader county- and state-level factors, specifically separating out how neighborhood demographics relate to eviction risk and ERA distribution from variation in effects by county and state. It also offers clear interpretation, making results easier to communicate to stakeholders. In both models, eviction filings and ERA payments are aggregated at the neighborhood level, while controlling for local demographic and housing conditions, neighborhood-level segregation, and relevant state policies such as eviction moratoria or tenant protections.[25]

25 Since tracts and counties nest within states, observations are not independent and require MLM techniques to account for this correlated variation among observations. Inter Intraclass Correlation Coefficient (ICC) values above 0.05 threshold justify the use of MLM techniques. As Appendix Tables B.1 and B.2 show, there is sufficient correlation between county and state variation to justify this approach—about 16% of the variation in ERA occurs between counties and another 16% occurs between states, while about 60% of the variation in eviction filing rates occurs between counties and nearly 5% between states. While county variation in eviction filing rates hovers around

In Analysis 1, we use the natural log of ERA payment totals at the neighborhood-level to induce a more normal distribution. All neighborhood demographic and housing market characteristic controls are mean-centered to improve model interpretability, which change the interpretation of model coefficients to be understood as relative to the average neighborhood. The primary explanatory variable of interest is a neighborhood's eviction risk, but controls for neighborhood demographics, such as the share of residents who are Black, Hispanic or Latino, Asian, unemployed, share of renters, and neighborhood income inequality, are included. Key neighborhood demographic variables are interacted with neighborhood eviction risk to understand how the impact of eviction risk on ERA funding may vary by neighborhood demographic context. For Analysis 2, which predicts eviction filing rates, the model specifications follow the county-level models in the previous chapter, except that three levels are included instead of two.

Both analyses in this chapter take advantage of the added flexibility of specifying random effects in MLMs. First, it is likely that each county and state has different baseline eviction filing rates or ERA payment levels. Therefore, random intercepts can be specified in each model to account for varying baseline rates of the outcome for each county and state. For example, in models predicting eviction filing rates, each county and state could have its own baseline eviction rate rather than relying on a sample-wide one. Second, effects can vary by county and state, reflecting how they vary in reality. In models predicting eviction filing rates, the neighborhood effects of ERA payments are of primary interest, and the effect of ERA dollars is assumed to differ across counties and states. Random slopes for the ERA variable can be specified to let its effect on eviction filings vary across counties and states, rather than assuming a constant effect. This approach accounts for potential variation in how strongly ERA dollars influence evictions across different counties and states.[26]

Findings

Analysis 1: ERA: Where did the money go?

<u>Descriptive Findings</u>

Exhibit 3.3 shows the distribution of ERA dollars (y-axis) by neighborhood HPRM eviction risk (x-axis) for 10 of the 40 states included in Analysis 1. Eviction risk is measured as an odds ratio, where values above one signify above average risk of eviction as compared to other tracts in the state. A regression line is fit to each state to illustrate the relationship of eviction risk with total neighborhood ERA dollars. Although this figure only presents a sample, every state except Idaho reports a positive relationship between neighborhood eviction risk and neighborhood total of ERA dollars—that is, higher eviction risk is associated with more ERA dollars.

Exhibit Targeting Assistance and Preventing Eviction: Tract-Level Analysis of ERA Distribution and Impact.16: HPRM Eviction Risk by ERA Dollars Distributed

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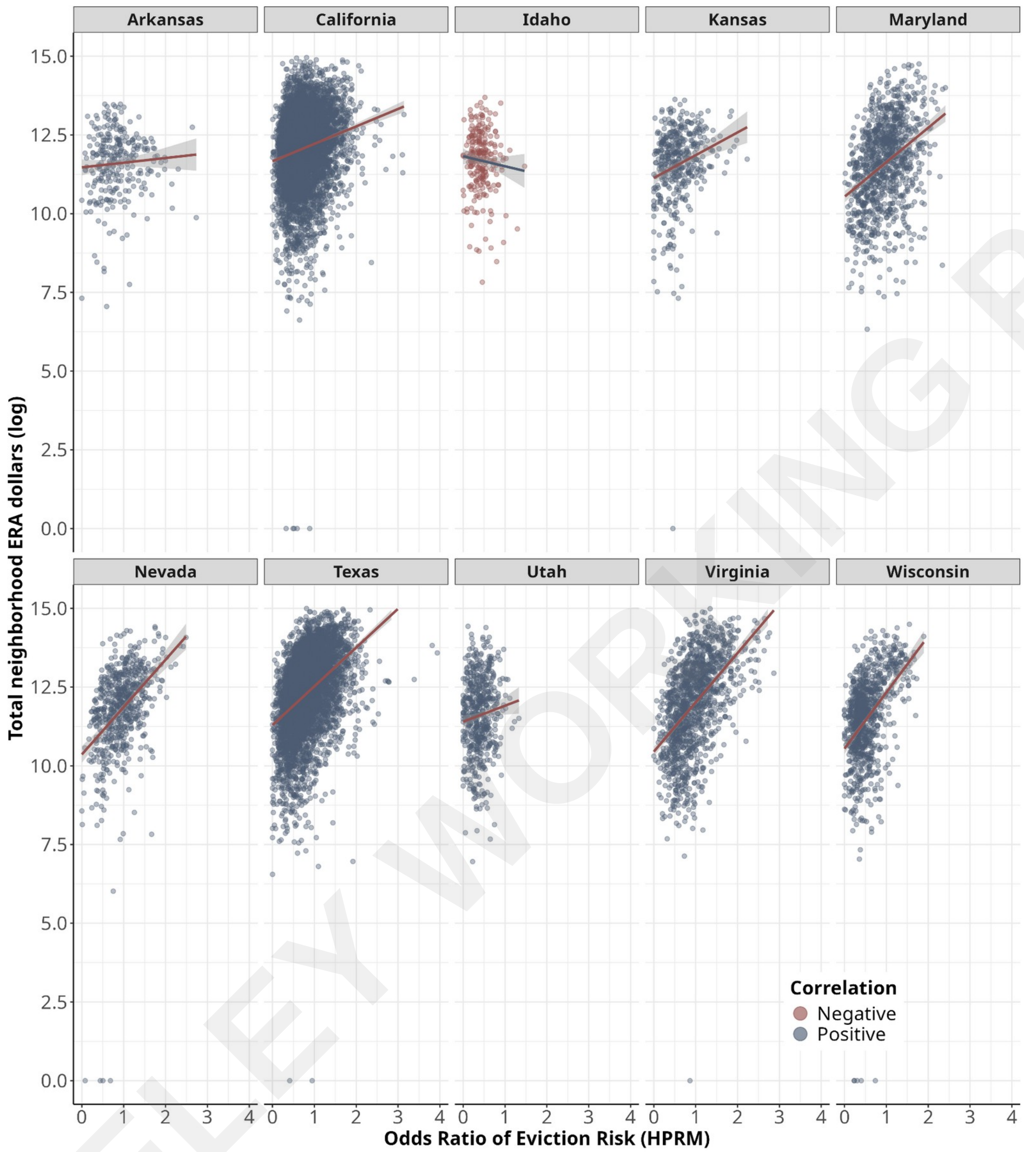
4%, between state-level variation is well above the 5% threshold and it is standard practice to group by all intervening levels (Snijders and Bosker 2011).

26 Beyond theoretical reasons, this report used likelihood ratio tests to verify that each added specification (random intercepts and random slopes) at each level improves model fit. Results are available in Appendix B.



Source: Figure based on authors' calculations using eviction data from the Legal Services Corporation and Emergency Rental Assistance payment data from the US Treasury. ERA values above $4 million are dropped to clarify the relationship.

<u>MLM Findings</u>

Exhibit 3.4 presents the results from the log-linear MLM that account for differences across neighborhoods. Model coefficients have already been transformed to odds-ratios for ease of interpretation: values of one have no effect, values above one signal a positive effect (increases in ERA dollars), and values below one signal a negative effect (decreases in ERA dollars). The first model regresses the outcome (total ERA dollars) on the explanatory variable of interest (eviction risk), providing a baseline estimate of the effect of eviction risk without any model controls. State-level tenant policy controls are added in Model 2, neighborhood demographic characteristics are added in Model 3, and controls for neighborhood inequality and unemployment are added in Model 4, which is the full model. Models 5-7 include interactions between eviction risk and share of Black residents, renters, and unemployed households, respectively. This analysis focuses on results presented in Model 4 since it contains all model

controls. Since all predictors are mean-centered, all coefficients are interpreted in relation to the average.[27] Overall, results indicate eviction risk is a strong and positive predictor of ERA distributed at the neighborhood level.

Exhibit Targeting Assistance and Preventing Eviction: Tract-Level Analysis of ERA Distribution and Impact.17: Primary results from multilevel regression models predicting ERA payments

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	97492.822 ***	101168.597 ***	112268.293 ***	111985.024 ***	116747.917 ***	111944.851 ***	112506.406 ***
	(11450.054)	(16826.736)	(17288.497)	(17212.059)	(18040.897)	(17340.725)	(17642.872)
Displacement risk	0.999***	0.999***	1.000	1.000	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Eviction risk	2.664***	2.685***	2.226***	2.194***	2.168***	2.167***	2.171***
	(0.206)	(0.210)	(0.133)	(0.131)	(0.112)	(0.131)	(0.130)
Total time period to eviction		0.964*	0.978†	0.978†	0.978†	0.978†	0.978†
		(0.014)	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)
Days of moratoria (z-scaled)		1.001	1.000	1.000	1.000	1.000	1.000
		(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Black			3.103***	3.030***	4.034***	3.161***	3.146***
			(0.420)	(0.408)	(0.671)	(0.447)	(0.431)
% Hispanic or Latino			1.629	1.522	1.452	1.493	1.484
			(0.486)	(0.454)	(0.419)	(0.441)	(0.430)
% Asian			1.544**	1.488**	1.407**	1.446**	1.475**
			(0.206)	(0.189)	(0.172)	(0.179)	(0.182)
% of renters			8.006***	8.351***	8.221***	8.584***	8.311***
			(0.673)	(0.699)	(0.680)	(0.678)	(0.690)

27 Meaning any one unit increase in a particular covariate is a one-unit increase above the mean.

Gini coefficient				0.468***	0.488***	0.472***	0.484***
				(0.073)	(0.073)	(0.072)	(0.075)
% unemployed				2.037**	2.144**	2.118**	3.810***
				(0.537)	(0.556)	(0.563)	(1.165)
Eviction risk× % Black					0.352***		
					(0.056)		
Eviction risk × % renters						0.631***	
						(0.083)	
Eviction risk × % unemployed							0.010***
							(0.007)
Num.Obs.	48069	48069	48069	48069	48069	48069	48069
BIC	148957.9	148976.8	141047.0	140962.4	140657.5	140877.7	140827.6
RMSE	1.09	1.09	1.01	1.00	1.00	1.00	1.00

† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

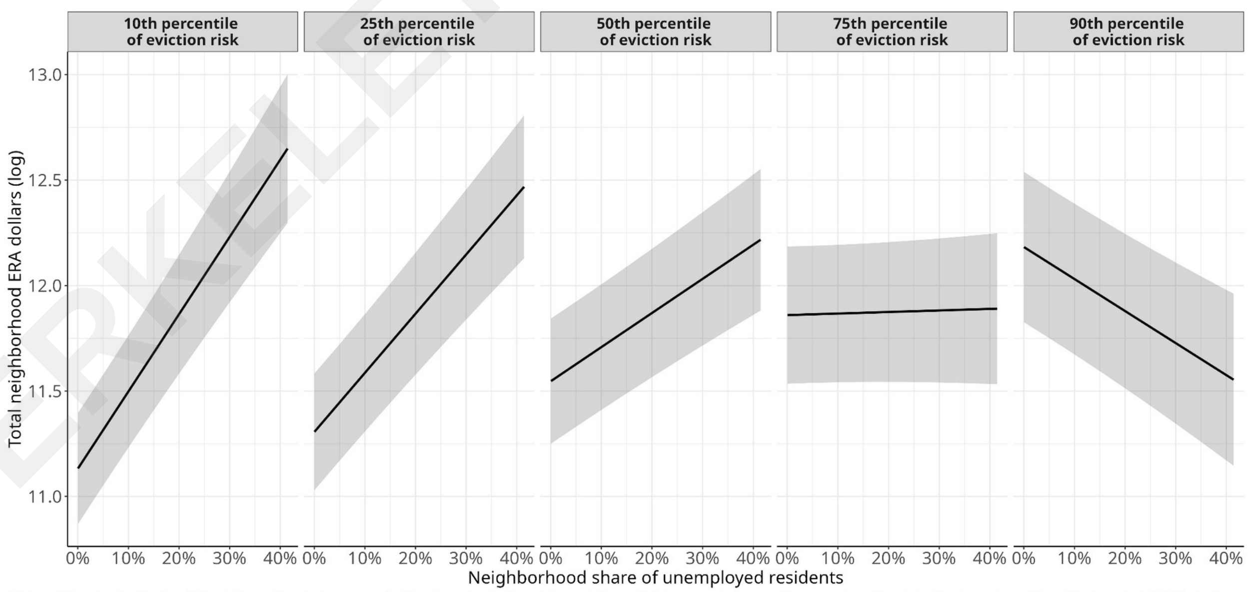
Notes: Baseline eviction rates and the effect of Eviction HPRM (eviction risk) vary by state and county (random intercepts and random slopes). Robust standard errors are in parentheses and are clustered by state. All continuous variables are grand mean-centered to facilitate interpretation. Intercept represents the average neighborhood total ERA payment.

Model 4 shows that neighborhoods with eviction risk one unit above the average received about 119% more total ERA dollars. This means that areas with higher eviction vulnerability compared to the typical neighborhood received more assistance. While displacement risk was also linked to ERA disbursement, this variable captures overall neighborhood churn of low-income residents, and the coefficient was very small and not statistically significant. These findings suggest ERA reached neighborhoods facing immediate eviction threat rather than those at risk of “soft” displacement.

Neighborhood demographics were strongly linked to how ERA funds were distributed. Neighborhoods with above average shares of Black residents, one of the most vulnerable demographics to evictions, received 200% more disbursements, even after controlling for other factors (Model 4). Neighborhoods with higher shares of Asian residents also received more disbursements—about 50% more—while the share of Hispanic or Latino residents was not a consistent predictor of the magnitude of ERA distributed in the neighborhood. Two additional strong predictors were neighborhood share of renters and unemployment rate, which were associated with over seven times and twice as much disbursements, respectively. Since only renters were eligible for ERA and tended to cluster spatially, areas with concentrated rental housing—over and above simple individual eligibility—received more ERA. Unemployment also played a key role, as job loss often drove the need for assistance. Finally, neighborhood economic inequality, as measured by the Gini coefficient, was linked to lower ERA distribution: more economically diverse areas received more assistance.

Next, neighborhood eviction risk is interacted with various neighborhood demographics to clarify how ERA disbursements vary by eviction risk and community context. Model 5 shows that neighborhoods with both high eviction risk and a large share of Black residents did not receive proportionally more ERA—the ‘bonus’ of increased ERA in high eviction risk neighborhoods was smaller in neighborhoods with higher shares of Black residents. Since Black residents are more likely to live in neighborhoods with higher eviction risk and received more ERA, this may reflect a saturation effect, or a diminishing responsiveness in resource allocation at the highest end of eviction vulnerability spectrum. Model 6 reports similar trends in predominantly renter neighborhoods. Model 7 results are similar but more dramatic, showing that eviction risk has a strong negative effect in neighborhoods with above average employment. Marginal effects plots in Exhibit 3.5 give a better sense of this relationship at various percentiles of eviction risk. While lower eviction risk (10th, 25th and 50th percentile) was associated with greater ERA distribution as neighborhood unemployment increased, neighborhoods with the highest eviction risk (90th percentile) actually saw less ERA distribution as neighborhood unemployment increases. These results suggest that high-unemployment and high-eviction risk neighborhoods received disproportionately less ERA. Although baseline levels of ERA are still high in these neighborhoods, a similar saturation effect likely means neighborhoods with very high concentrations of eviction risk and unemployment could have used more assistance.

Exhibit Targeting Assistance and Preventing Eviction: Tract-Level Analysis of ERA Distribution and Impact.18: Marginal effects of eviction risk on ERA payment by neighborhood share of unemployed residents



Notes: Marginal effects of the interaction between neighborhood eviction risk and the neighborhood share of unemployed residents show how the effect on total ERA dollars varied at the 10th, 25th, 50th, 75th, and 90th percentiles of eviction risk.

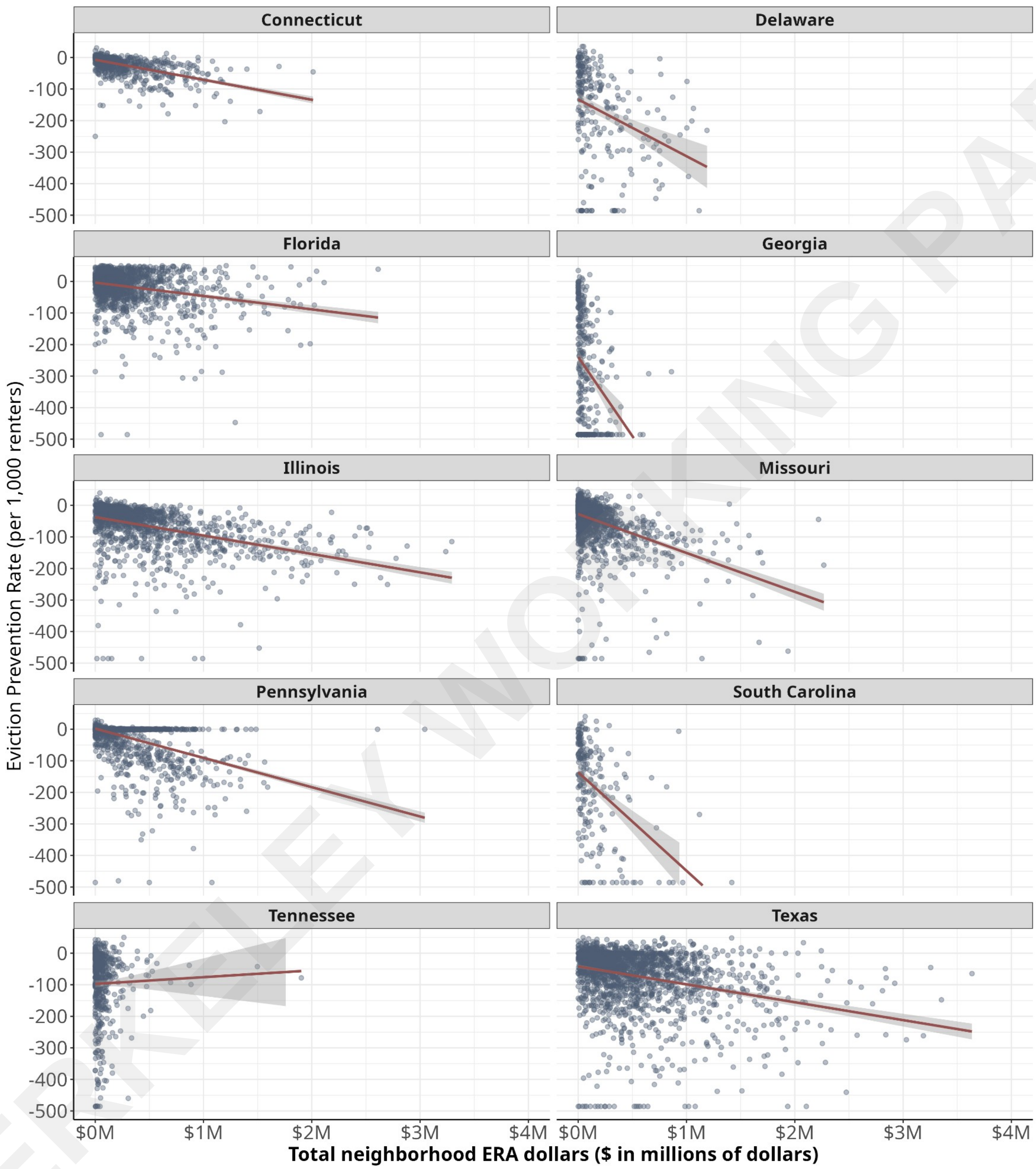
Taken together, these findings suggest that eviction risk was a key driver of ERA disbursement, and the impact of eviction risk varied across neighborhoods. ERA disbursement was concentrated in some of the most vulnerable neighborhoods—those with higher eviction risk and more Black, Asian, renter, and unemployed residents. While increases in ERA distribution in the most eviction-vulnerable neighborhoods did not continue to rise at the highest rates, baseline levels of ERA disbursement were still very high. The one exception was areas with very high unemployment *and* eviction risk. These neighborhoods saw stagnating or even negative effects of eviction risk on ERA disbursement levels. On the one hand, this raises questions about the effectiveness of targeting in high-eviction risk communities; on the other, it could also reflect disbursement saturation. Neighborhoods with high eviction risk *and* unemployment likely had more demand for rental assistance than could have been met by ERA programs. While ERA effectively reached neighborhoods in need, there is some evidence that programs may have struggled to fully meet the needs in the top percentile of the most vulnerable neighborhoods.

Analysis 2: EPR – What was ERA's impact on neighborhood eviction filings during the pandemic?

<u>Descriptive Findings</u>

A key objective of this analysis is to understand the impact of ERA on eviction filings. Exhibit 3.6 compares ERA payments and declines in eviction filing rates between the study period and the prior period (EPR) for the 10 study states. A linear regression line is fitted to visualize trends, with the x-axis limited to $4 million to exclude outliers. For most states, higher ERA payments are associated with greater reductions in eviction filings during the pandemic. The strength of this association varies across states. Georgia and South Carolina have the strongest negative relationship—greater ERA disbursements correlate with substantially greater reductions in pandemic-era filings. Several other states (e.g., Connecticut, Florida, Pennsylvania) show a more moderate inverse relationship between ERA and the EPR. Tennessee is an outlier in that only a few neighborhoods received substantial assistance; simple regression lines show no apparent relationship between ERA and the EPR.

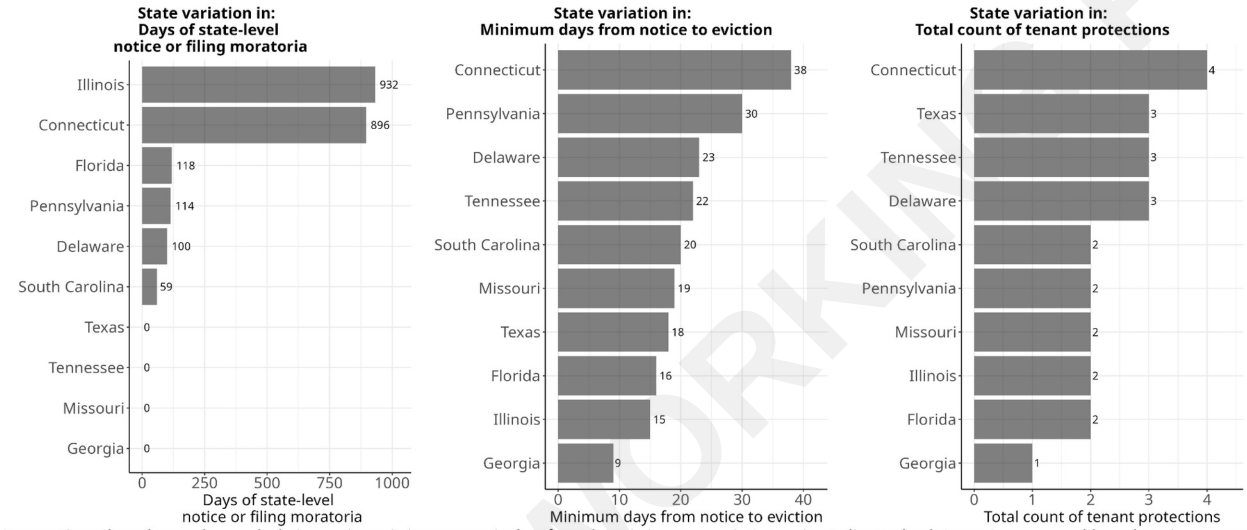
Exhibit Targeting Assistance and Preventing Eviction: Tract-Level Analysis of ERA Distribution and Impact.19: Eviction filing rates and ERA payments, by state



Source: Figure based on authors' calculations using eviction data from the Legal Services Corporation and Emergency Rental Assistance payment data from the US Treasury. ERA values above $4 million are droped to clarify the relationship.

Exhibit 3.7 below describes key contextual tenant protection policy environments that shaped eviction dynamics across states. The left panel highlights variation in the duration of state specific eviction moratoria, ranging from zero days in four states (Georgia, Missouri, Tennessee, and Texas) to 932 days in Illinois and 896 days in Connecticut. The middle panel illustrates variation in the minimum number of days it takes to evict a tenant in the respective state. This measure is designed to account for variation in state regulations that govern how quickly a landlord can evict a tenant and serves as an important proxy for tenant protections. Time-to-evict days range from 9 days in Georgia to 38 in Connecticut. Finally, the right panel shows the total count of tenant protections by state. Just as in the county model, these are measured as a count out of seven possible measures. Georgia has the fewest protections with one state-level tenant protections while Connecticut has the most with four.

Exhibit Targeting Assistance and Preventing Eviction: Tract-Level Analysis of ERA Distribution and Impact.20: State-level Variation in Moratoria and Tenant Protections



Source: Figure based on authors' calculations using eviction moratoria data from the Eviction Moratoria & Housing Policy: Federal, State, Commonwealth, and Territory dataset. Available here: https://doi.org/10.3886/E157201V2.

<u>MLM Findings</u>

The MLM results are presented in Exhibit 3.8. The first model regresses the outcome (EPR) on the explanatory variable of interest (total neighborhood ERA payment), providing a baseline estimate of the effect of ERA without any model controls. State-level tenant policy controls (Model 2), neighborhood demographic characteristics, and housing market context are then iteratively added. Model 3 includes all controls while Models 4 and 5 include interactions between ERA and tenant protection and neighborhood contexts. ERA is grand-mean centered to facilitate interpretation. The intercept provides a baseline eviction prevention ratio per 1,000 renters. For example, in Model 3, the average neighborhood (intercept) estimates 92 fewer eviction filings per 1,000 renters during the study period if all model covariates are held at their mean values.

The explanatory variable, ERA dollars, is logged to improve model fit and the coefficient can be interpreted as the change in eviction filing rates associated with a percentage increase in ERA disbursement.[28] For example, the Model 1 ERA coefficient is -6.903, meaning for every 10% increase (1.10) in ERA disbursement above the mean, there is a corresponding 0.658 fewer eviction filings per 1,000 renters:

$$-6.903 \times \log\left(1.10\right) = -0.658$$

28 In a linear-log model, a coefficient represents the change in the dependent variable for a percentage change in the independent variable. For example, to estimate the impact of a *p*% increase in payments, researchers multiply the coefficient by log(1 + *p*/100).

As expected, Exhibit 3.9 reports that more ERA dollars distributed to a neighborhood is associated with a greater reduction in eviction filing rates, even as the analysis controls for more potential confounding factors.

Exhibit Targeting Assistance and Preventing Eviction: Tract-Level Analysis of ERA Distribution and Impact.21: Primary results from multilevel regression models predicting eviction filings (EPR)

	Model 1	Model 2	Model 3	Model 4	Model 5
(Intercept)	-88.131**	-104.211***	-92.012***	-92.018***	-95.902***
	(30.511)	(31.045)	(25.534)	(25.625)	(25.989)
Total ERA dollars ($) (log)	-6.903***	-6.973***	-3.983**	-4.242**	-4.276**
	(1.945)	(1.930)	(1.406)	(1.480)	(1.443)
Days of moratoria (z-scaled)		14.952	-7.695	-8.413	-8.460
		(16.138)	(9.104)	(9.228)	(9.184)
Total time period to eviction		0.738*	0.351	0.357	0.537*
		(0.360)	(0.279)	(0.271)	(0.235)
Total count of tenant protections (z-scaled)		2.619	13.025	12.902	12.527
		(15.993)	(10.174)	(10.116)	(10.005)
% Black			-122.428***	-121.648***	-120.916***
			(20.402)	(20.636)	(20.249)
% Hispanic or Latino			-36.622*	-36.792**	-36.044*
			(14.272)	(14.181)	(14.403)
% Asian (log)			6.841***	6.792***	6.693***
			(2.019)	(1.999)	(2.023)
% of renters at 80% AMI			44.656*	45.066*	46.096**
			(17.865)	(17.852)	(17.619)
Theil's Information index			-16.620	-16.601	-20.009
			(25.562)	(25.520)	(25.350)
% enrolled in or graduated college (sqrt)			11.379*	10.718†	10.706†
			(5.589)	(5.554)	(5.487)
% unemployed			-31.999	-20.036	-29.839
			(26.685)	(30.063)	(26.877)
% rent-burdened households			-11.579**	-11.500**	-15.534***

			(3.859)	(3.871)	(3.007)
ERA x % unemployed				-15.085*	
				(7.374)	
ERA x % rent burdened households					-3.972**
					(1.445)
Num.Obs.	11988	11988	11988	11988	11988
BIC	135717.2	135727.3	134452.5	134452.9	134443.0
RMSE	67.86	67.86	64.40	64.39	64.36

† $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

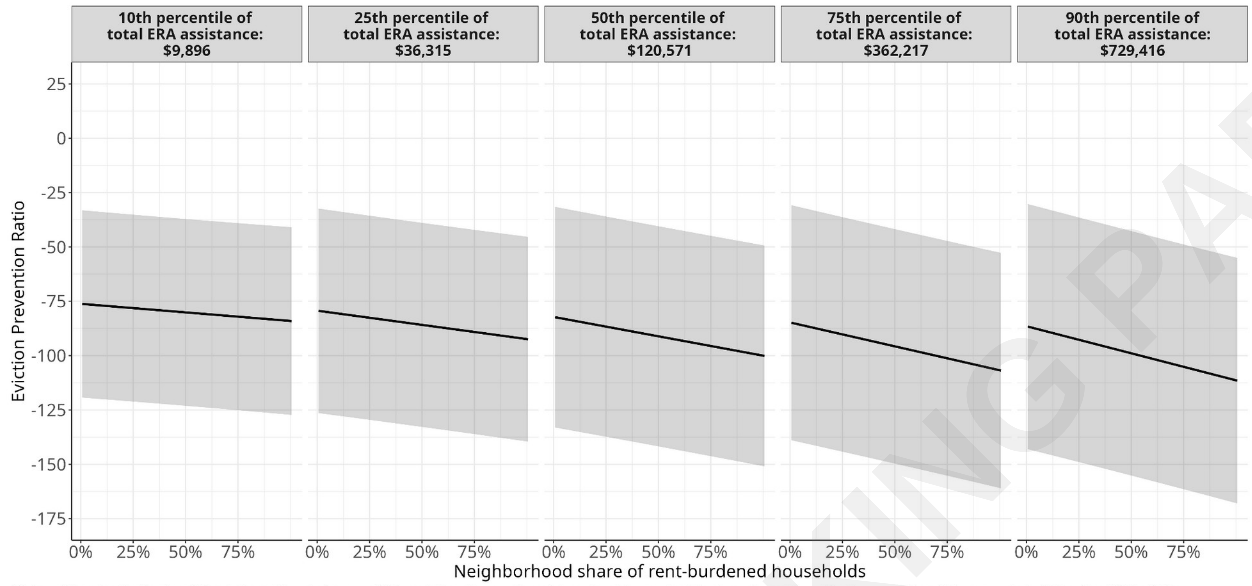
Notes: Baseline eviction rates and the effect of ERA varies by state and county (random intercepts and random slopes). Standard errors in parentheses and robust standard errors are clustered by state. All continuous variables are grand mean-centered to facilitate interpretation.

The interpretation focuses on Model 3, which includes all model controls. Holding all other neighborhood characteristics constant at their mean values, a one-unit increase in log ERA dollars above the neighborhood average ($269,263) is associated with 3.98 fewer eviction filings per 1,000 renters.

Several neighborhood characteristics are associated with fewer eviction filings during the study period, compared to the two years prior. Neighborhoods with higher shares of Black, Hispanic or Latino, and rent-burdened residents experienced fewer eviction filings during the study period. There are particularly strong effects for the share of Black residents in a neighborhood. A one percentage point increase above the average tract share of Black residents (~17%) is associated with 122.4 fewer eviction filings per 1,000 renters. In other words, if a neighborhood is average on all other factors, but 18% of its residents are Black instead of 17%, that neighborhood would be expected to have 214 fewer eviction filings (-92 + -122 = -214) compared to the pre-pandemic average. This is a large effect, suggesting that although Black residents are overrepresented in evictions in general, pandemic-era interventions had a significant impact in these communities. There is a similar but smaller reduction of eviction filings in neighborhoods with higher shares of Hispanic or Latino residents and rent-burdened residents.

A closer examination of ERA's impact on rent-burdened neighborhoods shows that the size of the impact on eviction filings varies by the share of neighborhood residents who are rent burdened. Exhibit 3.9 illustrates this point at the 10th, 25th, 50th, 75th, and 90th percentiles of ERA funding. Although modest, the slope of the line is slightly more negative at higher levels of ERA dollars in rent-burdened neighborhoods. In other words, the impact of ERA on reducing eviction filings grows as more funding is disbursed in rent-burdened neighborhoods.

Exhibit Targeting Assistance and Preventing Eviction: Tract-Level Analysis of ERA Distribution and Impact.22: Marginal effects of ERA on eviction filings by share of rent-burdened households

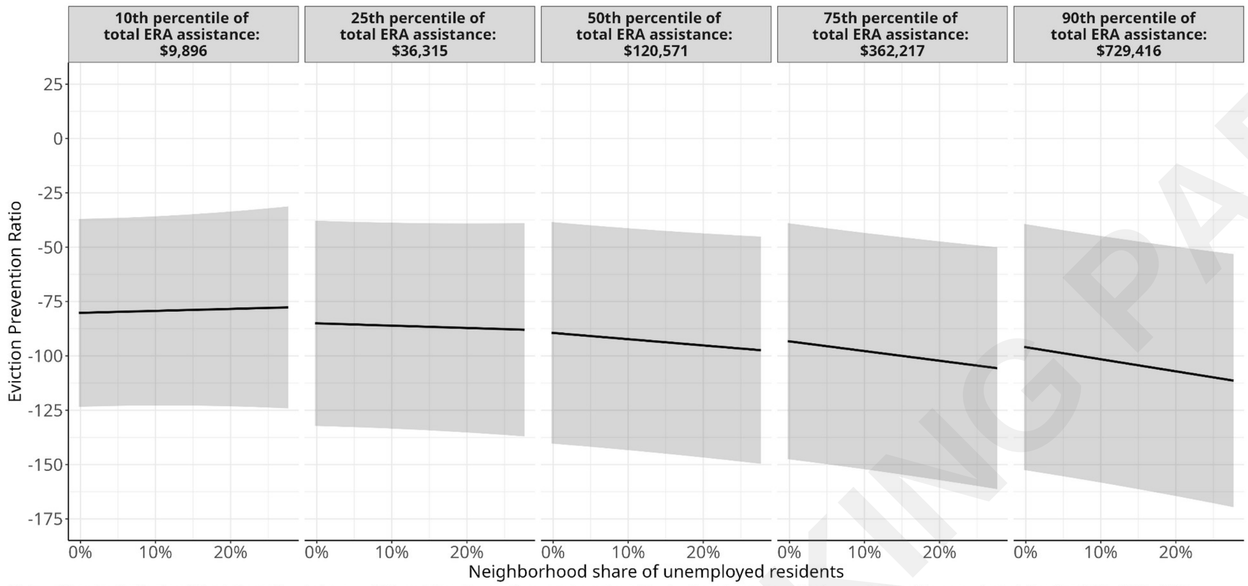


Notes: Marginal effects of the interaction between ERA and the share of rent-burdend households show how the effect on eviction filings varied at the the 10th, 25th, 50th, 75th, and 90th percentiles of total ERA assistance.

While several key variables were strong predictors of greater reduction in eviction filings during the pandemic, some demographic characteristics were associated with the reverse effect during the study period. For example, a 10% increase in the share of Asian residents corresponds to about 0.65 more eviction filings per 1,000 renters compared to the overall reduced volume of eviction filings during the pandemic. This effect should be interpreted with caution since the sample is missing many neighborhoods with large shares of Asian residents (e.g., neighborhoods in California and New York).

Finally, although the analysis did not find a statistically significant main effect of unemployment rates in the model, a significant effect emerged when interacting total neighborhood ERA dollars with the neighborhood share of unemployed residents. Exhibit 3.10 illustrates this point across different percentiles of ERA. The slope of the line is slightly positive at low values of ERA (e.g., 10th percentile) but becomes more negative at higher percentiles of ERA funding, suggesting that ERA has a larger impact on reducing eviction filings in neighborhoods with greater unemployment.

Exhibit Targeting Assistance and Preventing Eviction: Tract-Level Analysis of ERA Distribution and Impact.23: Marginal effects of ERA on eviction outcomes by share of unemployed residents

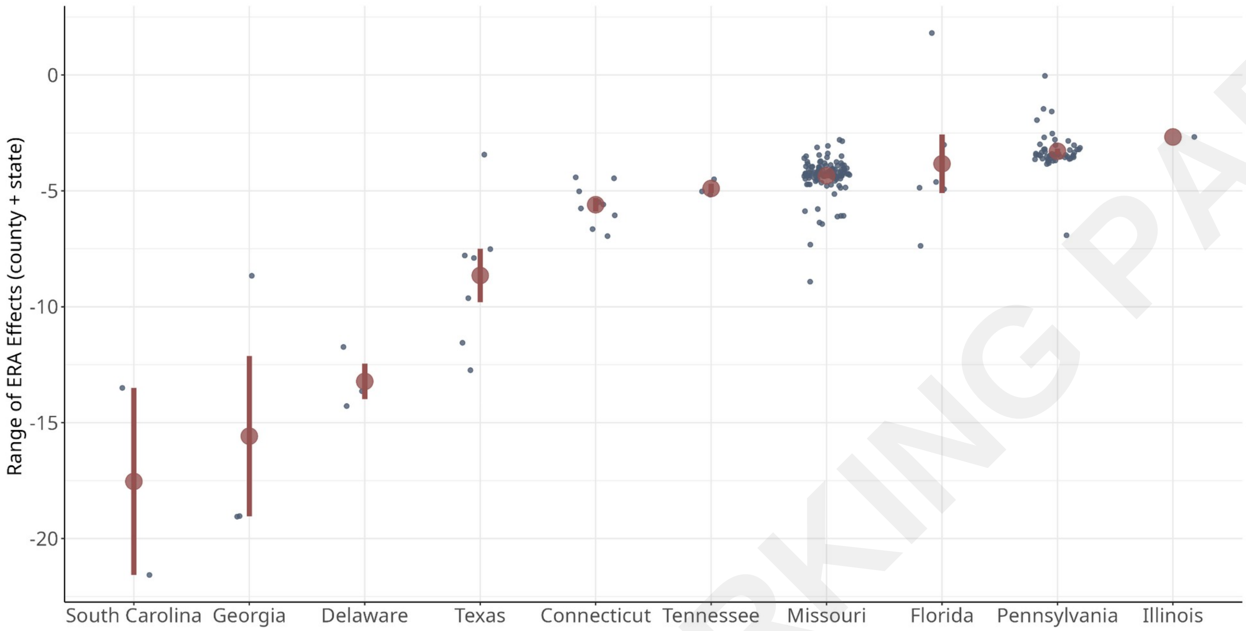


Notes: Marginal effects of the interaction between ERA and the share of unemployed residents show how the effect on eviction filings varied at the the 10th, 25th, 50th, 75th, and 90th percentiles of total ERA assistance.

The effect of state moratoria, total time to eviction, and total count of state-level tenant protections are not statistically significant in these models, similar to the finding in the county-level model.

A major benefit of using MLM to analyze ERA is the ability to see how the impact of ERA varies at the neighborhood level, taking into account its county and state context. Exhibit 3.11 illustrates the effects of ERA based on the county and state in which the neighborhood is located. Each blue point on the plot represents the combined effect of ERA each county and state has on a neighborhood. For example, if the ERA effect for a neighborhood in Harris County, Texas is -3.47, and the Texas state effect is an additional -4.43, then the total ERA effect for that neighborhood is -7.90 (calculated as -3.47 + -4.43 = -7.90). Red dots mark the median value for each state, with red lines marking the interquartile range. There is significant variation in ERA's effect across counties and states, indicating that ERA dollars had a stronger impact on neighborhood-level eviction filings in South Carolina, Georgia, or Delaware than in Pennsylvania, Florida, or Missouri. Many of the places where ERA had larger impacts also had fewer tenant protections, shorter moratoria periods, and larger shares of eviction-vulnerable populations. In other words, ERA reduced eviction filings in places where renters would otherwise not have had sufficient protections.

Exhibit Targeting Assistance and Preventing Eviction: Tract-Level Analysis of ERA Distribution and Impact.24: Random slopes of ERA by county and state



There are a few main takeaways from this analysis of eviction filings. First, more ERA disbursements to a neighborhood helped reduce eviction filings during the pandemic, and ERA's effect was amplified in neighborhoods with greater shares of unemployed and rent-burdened households. Second, neighborhoods with large Black and Hispanic or Latino populations reported fewer evictions, regardless of the total ERA distributed, likely due to the broad-based eviction moratoria in place during the pandemic. Finally, there was significant variation in the effect of ERA across states and counties. States that had the fewest protections and largest share of vulnerable populations had larger decreases in eviction filing rates associated with ERA.