Appendix to "Making Sense of Eviction Trends during the Pandemic" Hal Martin

I use a simple regression model to better understand what changes in eviction restrictions, rental assistance, and rent prices imply for eviction filing rates:

$$\begin{aligned} \ln(index+1)_{it} &= \alpha + \beta_1 f_{it} + \beta_2 p_{it} + \beta_3 r_{it} + \beta_4 D_{own} * \sum_{k \in 0, 1, 2} \frac{ERA_{i(t-k)}}{3} + \beta_5 D_{own} \\ &* \sum_{k \in 3, 4, 5} \frac{ERA_{i(t-k)}}{3} + \rho_i + \gamma_t + u_{it} \end{aligned}$$

The dependent variable $\ln(index + 1)_{it}$ is the natural log of the jurisdiction-level eviction filing index.¹ By exponentiating the resulting coefficients, I find the percent change in the eviction filing index predicted by a one-unit change in the variable of interest. Explanatory variables include the share of each month for which a jurisdiction faces a filing restriction (f_{it}), the share of each month for which a jurisdiction facing only a proceeding restriction (p_{it}), the three-month percent change in local rent prices (r_{it}), and grouped lagged values for rental assistance disbursements (ERA_{it}). The specific program features discussed above guide the expression of rental assistance in this model.

First, one expects that if rental assistance is conditional on complying with a short-term forwardlooking prohibition on eviction, or if tenants will receive renewals to short-term rental assistance after qualifying, the immediate effect of rental assistance would be to decrease eviction filings. To detect this effect over the relevant time window, I combine rental assistance payments in the same month, one month ago, and two months ago (k = 0,1,2) and express them as the average number of households receiving assistance in each of those months divided by the number of rental households in the market ($\sum_{k \in 0,1,2} ERA_{i(t-k)}/3$). For example, this variable would take the value of 1.7 percent for Philadelphia in September of 2021, where 3.2 percent of renter households received assistance in July, 1.2 percent in August, and 0.7 percent in September. I also construct a longer lag of the average market share of households receiving rental assistance three, four, and five months prior to capture the effect of even earlier rental assistance payments on eviction filings ($k \in 3,4,5$). This lag occurs beyond the forward-looking eviction prohibition window suggested in Treasury guidance, which provides suggestive evidence of what happens to tenants after that window expires.

Second, because I observe only aggregate disbursements from each city, county, or state with ERA funds, it is difficult to know how much disbursement from a higher-level political entity reaches one of its subdivisions, such as a city within a county or a county within a state, at any point in time. Because of this, I interact the grouped lags of rental assistance disbursements with an indicator of whether the jurisdiction in which I measure eviction filings is represented by its own dedicated ERA allocation (D_{own}). This allows me to separately estimate the relationship

¹ I transform the eviction filing index by adding 1 and taking the natural log. This permits the interpretation described while including meaningful values of zero, since $\ln(0)$ is undefined.

between eviction filings and ERA disbursements in jurisdictions with their own allocations, where impact may be more precisely reflected by disbursements, and those without.

The model includes jurisdiction fixed effects ρ_i and time fixed effects γ_t , which together absorb the variation in eviction filings that can be explained either by common time trends occurring across all places or by characteristics of each place that do not vary over time. For instance, the Centers for Disease Control and Prevention moratorium applied nationally for a specific period of time; its effect is included in the time fixed effects. Likewise, local policy regimes that favor landlords or tenants are included in the jurisdiction fixed effects to the extent that they are durable over time.

I cluster robust standard errors at the jurisdiction level and consider two specifications: one using ordinary least squares (OLS) and one using weighted least squares (WLS), wherein each jurisdiction is weighted by the number of rental units it contains.

Table A1 shows the results. The first column shows the regression coefficients, and the second column shows the exponentiated interpretation of the relevant coefficients that reflects the percent change predicted by a one-unit increase in each variable. Observations are weighted by the number of rental units in each jurisdiction. Because cities and counties with larger renter populations weigh more heavily in the regression, results are those to which the average renter across the sample is exposed.²

² Results are generally similar in an unweighted regression (not reported). Filing and proceeding restrictions have a similar effect, with higher precision on the estimate of the latter. The estimated impact of ERA assistance is more precise in the long term, though the effects in the short- and long-term are smaller. This difference suggests that larger markets are driving the results on the timing of ERA assistance. The effect of rent-price increases is similar.

	Coefficient	Change
Eviction Restrictions		
Proceedings	-0.350	-29.5%
-	(0.215)	
Filings	-0.965***	-61.9%
	(0.143)	
Rental Assistance		
Has own ERA allocation		
L(0,1,2).share renters helped	-0.192*	-17.4%
	(0.110)	
L(3,4,5).share renters helped	0.135	14.4%
	(0.0839)	
Does not have own ERA allocation		
L(0,1,2).share renters helped	-0.0182	-1.8%
	(0.0589)	
L(3,4,5).share renters helped	-0.126	-11.8%
	(0.124)	
3-month percent change in rent price	0.0203***	2.0%
	(0.00707)	
Constant	4.642***	
	(0.131)	
Observations	1,688	
R-squared	0.698	
Number of jurisdictions	64	
Time fixed effects	Yes	
Jurisdiction fixed effects	Yes	

Note: Observations are weighted by the number of rental units in each jurisdiction. Clustered robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1