Reviewer Appendix to Accompany:

The Effects of Nearby Tornadoes on Self-Protection Investments

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Appendix A1: Alternative Count Data Models for the Number of Rebate Requests

In Table A1, we assess the robustness of the results reported in Model 3 of Table 1 in the main paper across other types of count-data models and other specifications for the conditional mean number of rebate requests in a county-week. The estimates for Model 3 in Table 1 are reproduced the first column of Table A1. All coefficients represent the decimal percent change in the number of safe-room rebate requests in a county-week in response to a one-unit change in the independent variable.

In the second column of Table A1, we show the results for a zero-inflated negative binomial (ZINB) model, where the ZINB model is another way to allow for a type of overdispersion that might be present in our data. The ZINB is one of several existing count-data models that allow a separate data generation process to affect the frequency of zeroes in the distribution of the response variable (see section 3.2 of Greene (2007)). In brief, an additional probability point mass for the observed frequency of zeroes is modeled in the NB log-likelihood function as a function of a constant and other potential variables.

The second column of Table A1 specifies the probability point pass of the ZINB as a fixed constant (see "inflation constant"). We find the estimated value of the constant to be statistically insignificant, indicating a lack of statistical evidence for an above-expected occurrence of zero rebate requests after conditioning other the covariates in the model. For estimated values for the coefficient parameters, practically nothing has changed in comparison to the NB. A Vuong statistical test for nonnested models also confirms the lack of support for the additional performance that can sometimes be gained by adopting the ZINB. The statistic (ν) for the Vuong test is .005 and indicates inconclusive evidence to support of one model over the other. The Vuong test is computable under a model which does not provide standard errors that are clustered, which is the reason for the larger standard errors reported in column (2).

In addition to the ZINB, we report in column 3 estimates for a conditional fixed-effects negative binomial (FENB) estimator, proposed in Hausman, et al. (1984). Typical reasons for considering a

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¹ The Vuong test statistic has a limiting standard normal distribution when underlying conditions are met. In our case, large positive values of v favor the ZINB. Large negative value would favor the NB. The inconclusive region is values in (-1.96, 1.96).

conditional fixed-effects specification in a nonlinear maximum likelihood setting is a concern about the practical implementation of the optimization routine in the unconditional fixed effects model. For instance, many optimization routines have a more difficult time finding an acceptable solution when there is a very large number of dimensions over which to search for optimal parameter values. A conditional fixed-effects specification can also reduce concerns about incidental parameter bias, which is more likely to occur in the unconditional model when the number of time periods in the panel is relatively small compared to the number of groups (e.g., counties). In our case, with 240 weeks of observations per county, incidental parameter bias is likely not as much of a concern for Model 3 in Table 1. Moreover, Allison and Waterman (2002) perform a simulation study and find that the incidental parameters bias in the coefficient estimates of the unconditional fixed effects NB estimator may be negligible (although there may be some downward bias in the standard error estimates).

The only apparent differences we find between the NB and the FENB models are the slightly lower estimates for the lag coefficients in the FENB and an onset for the statistically significant temporal response in the NB that may begin a month sooner. Unlike traditional conditional fixed-effects models, however, the FENB also allows the inclusion of time-invariant variables in the specification of the conditional mean function of the count variable because the group-specific effects in the FENB are modeled in the dispersion and not directly as part of the conditional mean (Allison and Waterman (2002), Greene (2007)). The allowance for time-invariant variables in the specification of the conditional mean of the FENB means that the model can include unconditional county fixed-effects in the specification for the mean, along with the conditional fixed-effects in the dispersion specification of the model (see Greene (2008), pg. 918). We have tried this specification with county fixed-effects in both the mean and the dispersion, but found that this more-general model would not converge.

As we note in the body of the paper, the only F4 tornado recorded in Arkansas over the range of our data occurred in 2008. The last two columns of Table A1 report the estimates for the NB and the FENB when we include yearly binary indicators in the specification for the conditional mean number of rebate requests. The yearly indicators enable us to control for unobserved factors that could affect average household demand in a particular year (such as a single high-intensity tornado occurrence). If these

unobserved factors are captured by the lagged indicator variables for tornado activity, the inclusion of the yearly indicators could affect our estimates for the temporal response lag coefficients. The results for the NB (column (4)) and the FENB (column (5)) show that the additional controls produce noticeable effects on the other coefficient estimates. The contemporaneous effect of tornado activity in the concurrent week on rebate requests is negative and significant in both models. Likewise, column (5) shows an additional negative average effect during the first four weeks after the occurrence of a tornado. Among the "Year Indicators" in Table A2, across both the NB and the FENB models, the coefficient estimate specifically for the binary indicator for 2008 is large and significant. In comparison to 2006, the baseline yearly indicator excluded from these specifications, the year 2008 exhibits roughly a 67 percent greater number of safe-room rebate requests across the state.

The most important differences resulting from the inclusion of yearly indicators in the specification for the NB and FENB models is the reduction in the magnitude of the temporal response lag coefficients. In what appears to be the peak of activity during weeks 9 through 12 after a tornado occurrence, the magnitude for the coefficient estimate decreases by roughly 17 percentage points. Our analysis is limited to the five years of available data and only one F4 tornado occurrence (and no F5's), leaving our estimates susceptible to small sample bias. For these reasons, we suspect that the coefficient estimates on the temporal lags of tornado activity in Models 1 and 2 are a conservative estimate. The magnitudes of the temporal responses that would exist across a larger number of years of observations would likely be larger with a greater sampling of more intense tornadoes, although the direction of bias is not entirely clear since the repeat frequency of tornadoes in a particular area decreases with intensity. We believe that our results for the temporal response estimates in Tables 1 – 3, which do not include year indicator variables, are best interpreted as reflecting the average tornado intensity effects over the time period of analysis.

Table A1 – Alternative Non-Parametric Temporal Specifications for Tornado Activity within 50 mi. of County Centroids

Dependent variable: Weekly number of safe-room rebate requests by county (c)

ESTIMATED	(1)	(2)	(3)	(4)	(5)
PARAMETERS	NB (same as	ZINB without	FENB	NB with yearly	FENB with yearly
	Model 3 in Table 1)	clustered errors		indicators	indicators
Tornado activity within 50	14010 1)	CHOIS			_
miles (=1)					
$T_{c,8/5}^{50}$	0.00301	0.00301	0.0641	-0.0542	-0.00623
2,075	(0.051)	(0.049)	(0.922)	(-0.931)	(-0.109)
$T_{c,4/1}^{50}$,				
- c,4/1	0.0395 (0.679)	0.0395 (0.655)	0.0670 (1.182)	-0.0517 (-0.950)	-0.0275 (-0.529)
T^{50}					
$T_{c,0}^{50}$	-0.143	-0.143	-0.0761	-0.236***	-0.174**
50	(-1.593)	(-1.530)	(-0.946)	(-2.652)	(-2.073)
$T_{c,-1/\!-\!4}^{50}$	0.121*	0.121**	0.0388	-0.0192	-0.0847*
	(1.832)	(2.044)	(0.563)	(-0.299)	(-1.679)
$T_{c,-5/-8}^{50}$	0.382***	0.382***	0.371***	0.212***	0.186***
	(5.790)	(6.139)	(6.462)	(2.932)	(2.947)
$T_{c,-9/-12}^{50}$	0.509***	0.509***	0.448***	0.322***	0.285***
C,-9/-12	(7.070)	(8.379)	(5.202)	(5.099)	(4.388)
$T_{c,-13/-16}^{50}$,	` ,		, ,	, ,
<i>I</i> _{c,-13/-16}	0.341***	0.341***	0.362***	0.217***	0.226***
50	(5.761)	(5.898)	(5.852)	(3.273)	(4.272)
$T_{c,-17/-20}^{50}$	0.283***	0.283***	0.232***	0.183***	0.139***
	(4.835)	(4.861)	(5.024)	(2.988)	(3.115)
$T_{c,-21/-24}^{50}$	0.306***	0.306***	0.283***	0.209***	0.193***
	(5.253)	(5.202)	(5.029)	(3.484)	(3.177)
$T_{c,-25/-28}^{50}$	0.359***	0.359***	0.294***	0.290***	0.257***
0, 20, 20	(6.403)	(6.105)	(4.315)	(5.525)	(4.710)
$T_{c,-29/-32}^{50}$	0.197***	0.197***			
- c,-29/-32	(3.198)	(3.504)	0.140*** (2.872)	0.170** (2.564)	0.117* (1.850)
T^{50}		` ,			
$T_{c,-33/-36}^{50}$	0.118**	0.118**	0.0883	0.114*	0.115*
50	(2.075)	(2.132)	(1.373)	(1.850)	(1.930)
$T_{c,-37/-40}^{50}$	0.00642	0.00642	0.0306	0.0149	0.0711
	(0.152)	(0.116)	(0.694)	(0.319)	(1.407)
Monthly indicators (=1)	0.200	0.200	0.110	0.255*	0.161
February	0.209	0.209	0.119	0.255*	0.161
March	(1.429) 2.035***	(1.499) 2.035***	(0.922) 1.634***	(1.705) 2.153***	(1.462) 1.788***
Waten	(8.986)	(10.264)	(7.969)	(9.441)	(8.681)
April	3.093***	3.093***	2.470***	3.423***	2.829***
	(12.291)	(13.010)	(12.001)	(12.977)	(13.066)
May	2.286***	2.286***	1.699***	2.648***	2.088***
•	(11.024)	(11.150)	(10.485)	(11.670)	(10.027)
June	2.803***	2.803***	2.176***	3.301***	2.686***

		(11.395)	(13.167)	(11.140)	(11.881)	(11.998)
Jul	lv	2.376***	2.376***	1.852***	2.733***	2.197***
0 67	-,	(9.623)	(12.138)	(9.930)	(10.318)	(10.121)
Aı	ıgust	1.719***	1.719***	1.461***	1.908***	1.683***
710	15ust	(8.123)	(9.520)	(8.994)	(8.488)	(8.501)
Se	ptember	0.570***	0.570***	0.497***	0.634***	0.582***
~~.	F	(3.915)	(4.045)	(3.869)	(4.243)	(4.131)
Oc	ctober	0.565***	0.565***	0.586***	0.611***	0.639***
		(3.751)	(4.101)	(3.964)	(3.901)	(4.493)
No	ovember	0.0800	0.0800	0.104	0.0912	0.119
		(0.750)	(0.655)	(1.037)	(0.841)	(1.075)
$\mathrm{D}\epsilon$	ecember	0.126	0.126	0.156	0.142	0.162*
		(1.080)	(1.037)	(1.568)	(1.204)	(1.694)
Year Indi	cators (=1)	, ,	,	, ,	,	, ,
20	007	-	-	-	0.0770	0.0944
					(0.868)	(1.150)
20	008	-	-	-	0.665***	0.679***
					(4.884)	(5.810)
20	009	-	-	-	0.184*	0.162
					(1.867)	(1.608)
20	010	-	-	-	0.0363	0.0841
					(0.354)	(0.826)
Constant		-0.928***	-0.928***	-0.793***	-0.939***	-0.816***
		(-25.587)	(-14.445)	(-7.648)	(-19.397)	(-7.690)
County fix	ed effects	Uncond.	Uncond.	Conditional	Uncond.	Conditional
Overdisper	rsion	0.341**	0.341***	-	0.348**	-
		(2.516)	(8.002)		(2.145)	
Inflation co	onstant	-	-38.02	-	-	-
			(-0.000)			
Vuong test	t statistic (v)	-	.00500	-	-	-
# of observ		18,000	18,000	17,760	18,000	17,760
Log likelih		-11,202	-11,202	-11,025	-11,156	-10973
# of counti	es	75	75	74	75	74

Notes: Coefficient estimates represent the average percentage change in weekly number of safe-room rebate requests in a county for a unit change in the independent variable. *** p<0.01, ** p<0.05, * p<0.1.; z-statistics with standard errors clustered by county are reported for the NB and ZINB models; standard errors are bootstrapped for the FENB models. A significant positive value for the dispersion parameter indicates overdispersion after conditioning on the independent covariates. The Vuong test statistic compares the fit of a NB to the ZINB. Values between -1.96 and 1.96 indicate inconclusive evidence to support the favor of one model.

Appendix A2: Estimation Results for Effects on Safe-Room Costs

In Table A2, we report the results when we adapt a non-parametric temporal response function for specification **Error! Reference source not found.** to model the costs of safe-room installation for the rebate requests during the period of our analysis. The dependent variable is the mean cost (in nominal dollars) of safe-room installations in a county-week. This variable is right-censored for 3,172 observations at \$2,000. There are 14,539 county-week observations that have missing values, indicating that there were zero funded rebate requests in those county-weeks. There are a total of 289 (approximately 10%) of applications for which reported safe-room installation costs are not top-censored, i.e., the mean cost of funded safe rooms is between \$0 and \$2000.

In Models 1 through Model 3 in Table A2, we use a random effects Tobit regression for the top-censored price variable to obtain estimates of the effects of recent nearby tornado activity on safe-room expenditures. Model 1 uses regressors which are identical to those used in Model 3 of Table 1 in the main paper. The estimates of the temporal lag coefficients from Model 1 do not have any distinguishable pattern within the 40-week period of the temporal response as they do in Model 3 of Table 1. We do find for some lagged periods a small and significant decrease in costs. However, these effects fail to maintain significance throughout the rest of our models.

In Model 2 of Table A2, we include year indicators to control for any potential omitted variable bias from abnormal years of tornado activity or the availability of safe-room installations that might affect our estimates in Model 1. We do not find any differences in the temporal lag coefficients in comparison to Model 1 but do find that the overall year-to-year pattern in the coefficient estimates for the year indicators to be increasing. In Model 3, we adjusts costs for inflation and find the apparent upward yearly trend in the average costs of safe-room installations is almost certainly due to average price inflation during this time period. It may be that the high-level of censoring in the data has resulted in estimates that are biased due to the relatively small 10% of applications for which safe-room installation costs are not censored. In Model 4, we perform a linear fixed-effects regression on counties for those 289 uncensored observations and include year and month-of-year indicators. The lag coefficients, again, do not suggest any strong pattern in the immediate temporal response of prices to recent activity. The only noteworthy result in

terms of the year indicators is a decrease in prices in 2008, a year with an significant tornado event, possibly indicating that contractors have responded to the demand increase over previous years by raising prices, and a decrease in prices in 2010.

Table A2 – Left- and Right-Censored Random Effects Tobit Models for the Costs of Safe-room Installations

Dependent variable: Mean installation costs for funded safe-rooms by county-week (1) (2) (3) (3) Random Random Random Linear **Effects Effects Effects** Fixed **COEFFICIENTS Tobit Tobit Tobit Effects** Tornado activity within 50 miles (=1) $T_{c,8/5}^{50}$ -43.13 -47.81 -46.18 -40.00 (-0.732)(-0.847)(-0.807)(-0.891)-9.340 -7.348 -7.663 52.84 (-0.173)(-0.144)(-0.153)(1.132) $T_{c,0}^{50}$ 8.556 0.790 0.739 -141.8 (0.026)(0.007)(0.008)(-0.811)-66.39* -78.11** -75.77* -27.46 (-1.664)(-1.985)(-1.782)(-0.561) $T_{c,-5/-8}^{50}$ -29.67 -6.187 -30.87 -42.75 (-0.107)(-0.618)(-0.486)(-1.146) $T_{c,-9/-12}^{50}$ 30.28 32.47 30.74 22.00 (0.768)(0.911)(0.813)(0.899) $T_{c,-13/-16}^{50}$ -33.17 -41.48 -39.17 19.14 (-0.937)(-1.218)(-1.167)(0.528) $T_{c,-17/-20}^{50}$ -82.76** -69.29* -67.12* 34.10 (-2.403)(-1.782)(-1.738)(1.038) $T_{c,-21/-24}^{50}$ 17.94 16.82 16.35 54.74 (0.417)(0.501)(0.366)(1.333)-78.43* -62.58 -64.89 -26.69 (-1.756)(-1.400)(-0.978)(-0.958) $T_{c,-29/-32}^{50}$ 34.02 67.65 64.94 11.81 (0.820)(1.284)(1.441)(0.298) $T_{c,-33/-36}^{50}$ -93.05** -58.58 -56.22 36.74 (-2.371)(-1.359)(-1.326)(0.947) $T_{c,-37/-40}^{50}$ -52.77 -27.97 -8.110 -26.11 (-1.018)(-0.532)(-0.528)(-0.225)**Year Indicators**(=1) 2007 18.64 73.22 -65.59 (1.183)(0.279)(-0.989)2008 149.2** 23.74 -72.98* (2.557)(0.415)(-1.855)2009 164.0** 44.22 7.827 (2.043)(0.524)(0.138)2010 235.1*** 85.78 -93.74** (1.057)(2.797)(-2.199)2.633*** 1.786*** 2.806*** 2.605*** Constant

	(26.590)	(19.874)	(18.279)	(20.045)
Inflation-adjusted costs	No	No	Yes	Yes
Year indicators	No	Yes	Yes	Yes
Month indicators (seasonality)	Yes	Yes	Yes	Yes
County random effects	Yes	Yes	Yes	Yes
σ_u (std. dev. of county effects)	304.4***	293.8***	282.8***	131.0**
	(8.072)	(7.601)	(7.917)	(2.443)
$\sigma_{_e}$ (std. dev. of model error)	410.8***	404.7***	389.5***	188.0***
	(11.946)	(11.814)	(10.488)	(9.379)
Observations	3,461	3,461	3,461	289
Log likelihood	-2,659	-2,648	-18,411	-1,950
Number of counties	74	74	74	50

Notes: z-statistics with bootstrapped standard errors are reported. *** p<0.01, ** p<0.05, * p<0.1. There are 14,539 observations with no price information (i.e., there were no shelter installations that received rebates in those county-weeks), 3,172 observations that are right-censored at \$2,000, and 289 uncensored observations. All models also include 11 monthly dummy variables, none of which is individually statistically significant in any model.