The Effects of Extreme Weather Events on Self-Protection Investments

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Focus of paper:

1. **Heightened demand and potential explanations for observed behavior (fear, trauma, stress, anxiety, availability bias and forgetfulness)**
2. **How is observed heightened demand affected by potential constraints in the system**
3. **What is the appropriate policy intervention when constraints exist, if any?**
    a. **Discussion must consider that fact that individuals may already be under or over-estimating the objective risk**

Abstract

We use a unique data set from a tornado shelter (safe-room) rebate program in Arkansas from 2006 through 2010 to examine the role of risk perceptions in stimulating homeowner investments in self-protection. Using empirical models that explore both extensive non-parametric specifications and streamlined parametric forms for lagged responses, we find that the decision to self-protect depends clearly upon both the recency and the proximity of tornado events, as well as on average education and income levels in the county in question. The pulse in self-protection investment after a tornado is relatively large yet short-lived and relatively local, and there is some evidence that short-run supply constraints limit the expression of peak demand over time and across space. Our findings suggest the potential importance of self-protection investments as an adaptive response to changes in the severity and spatial extent of extreme weather risks that may result from climate change. We also highlight the role that rebate policy design may play if the goal is to encourage self-protection investments at least cost.

Keywords: climate change, natural hazards, severe weather, extreme events, risk perceptions, self-protection investment, averting behavior

JEL Classifications: D81, D83, Q51, Q54

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1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) and other researchers predict that a continuation of climate change is likely to produce more measurable changes in extreme weather events across the world.[2,3] Understanding the overall economic impact of changes in extreme weather events is a challenge, however, because individuals and households will gain new information about changes in the objective risks of extreme weather and then may choose to adapt their current behavior to reduce the risks from future events. If individuals choose to adapt, the costs of extreme weather may become less certain if adaption is not easily observed or if it is difficult to place a monetary value on the actions taken. Further, if adaptation is observed to at least partially occur due to individuals over estimating the objective dangers of climate change then the costs of adaption could be larger than under a scenario with no adaption. One type of adaptive behavior that individuals may adopt is self-protection—a response to risk exposure that reduces the probability of a loss from a future event (Ehrlich and Becker (1972)). The goal of our research is to characterize the temporal and spatial patterns of self-protective behavior in the response to one significant type of extreme weather event (tornadoes), constraints in the supply of services and infrastructure for self-protection, and the role, if any, that government policy might have in the efficient or cost-effective facilitation of self-protection efforts.

We use five years of daily observations on applications to a well-publicized government safe-room rebate program in the U.S. state of Arkansas, and model these applications as a function of tornado activity within (and near) 500 miles of households' counties of residence. We use these models to reveal the temporal and spatial effects that extreme weather events may have on individuals' perceived risks and their subsequent self-protection behavior. Our results show a significant jump in safe-room rebate

[2] The report, "Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation," is to be officially released to the public in February 2012. A pre-release version of the report can be found at http://www.ipcc.ch/pdf/special-reports/srex/SREX_FD_SPM_final.pdf.

[3] Projected changes include, for example, increased frequencies for heavy precipitation (cite), longer durations for heat waves (cite), and greater maximum wind speeds for hurricanes (cite). Recent evidence suggests that California's on-going drought has been made more severe than what would have occurred without climate change (cite).

requests to a state rebate program in the weeks that follow an episode of nearby tornado activity, reaching a maximum of between 25%-50% above the usual county-level weekly average rebate requests during the ninth through twelfth weeks following nearby tornado activity. The magnitude of the effect then declines over the ensuing ten months until rebate requests are restored to their pre-tornado average levels. Notably, this pattern of investment in self-protection is likely inconsistent with any *actual* changes in the objective risks of tornadoes, since tornado strikes are essentially random within broad tornado-prone areas. This suggests that household motivation for self-protection behavior does not conform entirely to standard economic models of rational choice.

We also find evidence that short-run supply constraints may temper what would otherwise be an even larger immediate increase in safe-room installations after a nearby tornado occurrence. Households in closer proximity to the path of a recent tornado must go farther afield, on average, to find an available contractor. They are also more likely, in these circumstances, to hire an “off-brand” contractor, or to install the safe-room themselves, suggesting that economies of scale (and from experience) are not being exploited. A nearby tornado could also increase demand for higher-quality and more expensive safe-rooms. Our data on safe-room installation costs are heavily censored so we cannot robustly examine binding supply constraints with temporal and spatial information on prices.

If self-projection is limited by supply constraints, better designed incentives for consumers or suppliers might lead to a greater amount of self-protection for the individuals most in need. Policies that incentivize self-protection behavior could be designed to smooth demand over time and across geographic space so that "peaking capacity" among local contractors is less likely to be exceeded. While such policies would come at a cost, they could have an overall net benefit for society by reducing injuries and fatalities from extreme weather events.

2. Conceptual Framework

There are many ways in which individuals and households might adapt to perceived risks from tornadoes and other extreme weather events. Households have been observed after a recent nearby hurricane to increase insurance coverage against the potential damage of future unexpected hurricanes (Browne and Hoyt (2000)). Farmer's in the Midwestern U.S. increase insurance coverage after farmland droughts (cite) and households have been observed to increase home insurance coverage due to nearby forest fires in the Western U.S. (cite). These strategies reduce the potential loss to one's economic welfare from property damage. If individuals on the other hand have a greater preference to avoid injury and death from an extreme event then self-protection strategies, i.e., strategies for reducing the probability for a loss, might represent a more valuable alternative.

The preferred method of self-protection will be motivated by opportunity costs. Existing findings for self-protection strategies in response to tornadoes includes migration (Duquette and Cameron (2010)) and upgrades or improvement to housing infrastructure (Sutter and Poitras (2010)). [5] If the disutility from changes in perceived risks to one's life and welfare is insufficient to overcome the threshold represented by direct and indirect costs of moving or buying a better-constructed home, households will find that "sheltering in place" with an residential shelter is a better alternative. For tornadoes, individuals can self-protect by installing either an in-ground or an above-ground safe-room or shelter. For these shelter-in-place households, a lower bound on the loss of utility from greater perceived tornado risks is then the amount of money that households are willing to spend on self-protection, i.e., to make their dwelling safer.[7]

Our data show that demand for self-protection spikes after a tornado, which seemingly contrasts what would be predicted by a standard economic model of rational choice. That is, households fully informed about the randomness of tornado strikes across tornado-prone areas would not, under the

[5] Sutter and Poitras (2010) note that individuals may also invest in housing infrastructure that is less vulnerable to extreme weather. Similar to migration, switching to an alternative housing choice in the same local area may require that the household incur substantial direct and indirect costs. Observed self-protection costs in the form of trading up to a more tornado-resistant house in the same area might represent only a small fraction of the aggregate utility loss from an increase in perceived tornado risks because of all the other households whose utility is decreased, just not sufficiently to precipitate relocation to a different house.

[7] The degree to which self-insurance might affect our results in unclear and left for further research. As Ehrlich and Becker (1972) demonstrate in a theoretical model that the availability of public protection and market insurance do not necessarily reduce investments in self-protection. There is little empirical evidence on the potential relationship between these two adaptive mechanisms.

standard model, be expected to systematically change their demand for self-protection after a tornado event. A reason for the fluctuation in observed self-protection could be a change in individuals' risk perceptions in response to an event. The stress and trauma of a natural disaster has be found to lead individuals to have feelings of anxiety (cite) and fear (cite). If these feelings are present after an event, the objective risks of future events may have less of an impact of current decision-making. Specifically in regards to tornadoes, Suls et al. (2012) find individuals' *perception of vulnerability* to a future tornado occurrence is affected by the amount of elapse time and an individual's physical proximity to the last event.

Another possible explanation for observing heightened demand in self-protection after a tornado event is if individuals were not fully informed about the objective risks prior to the event. This is plausible in the case of tornadoes and evidenced in the case of other extreme weather events because these events occur relatively infrequently within any given locality. For instance, Hallstrom and Smith (2005) find that housing prices after Hurricane Andrew had lower year-to-year appreciation rates in flood-risk zones where individuals were already more likely informed about the objective risks of a flooding. Likewise, Kousky (2010) finds the relative decline in housing prices in St. Louis County, Missouri after the devastating 1993 Midwest floods was smaller in areas where homeowners were less likely to be informed of the flood risks.[8]

A consequence of individuals lacking the true objective risks of tornadoes can lead to "availability bias" (Tversky and Kahneman (1973, (1974)) in which individuals respond too much or too little to the objective threat of a future tornado based upon their *ability to recall* previous tornado occurrences. The degree to which availability bias could affect response might depend on individual behavior traits and characteristics of the events. For instance, Gallagher (2010) studies the effect of flood-risk information on observed response and finds that a learning model for flood events that incorporates a rate of forgetfulness is better at explaining temporal responses of insurance uptake after flood events than

[8] In the twelve years following the flood, however, there was no statistically significant (return) trend in the year-by-year relative decline of housing prices in areas where homeowners were less likely to be aware of the risk.

similar models that do not.[9] This finding suggests that if individuals tend to quickly forget past extreme weather, traces of availability bias in self-protection behavior would diminish over time. That such temporal behavior may still be considered rational is argued by Becker and Rubinstein (2011), who find evidence of changing temporal patterns in self-protection due to infrequent terrorism events in Israel. They argue the observed responses are because individuals at least partially recalibrate based on economic incentives and their "mental human capital investments."[10, 11]

Additional findings that support availability bias as a mode of behavior in response to extreme weather include evidence that insurance coverage and housing prices for individuals and households in areas that were designated, *a priori*, flood-prone deviate less from previous levels and/or return more quickly to previous levels after a flooding event (Browne and Hoyt (2000), Kousky (2010)).[12] Some experimental studies have also found that choices by individuals to self-protect against events with negative consequences are affected by the recency of a similar event (e.g., Shafran (2011)).[13]

The importance of information about the objective risks of tornadoes is also evidence by Zahran et al. (2012) (Sutter's work?) who find that the day of week that a hurricane or tornado event occurs can differentially affect the number of observed casualties. Specifically, Zahran et al. find hurricanes produce less casualties on weekends than on weekdays and tornadoes produce relatively more on weekdays. This seemingly paradoxical occurrence appears to be partially a result of the increased lead-times in the

[9] The potential diminishing rate of responses presents a challenge to researchers trying to measure and understand individual behavior to infrequent weather events. If the time-delineated data in a study is too aggregated in comparison to the rate at which individuals and households may return to a level of normal behavior then 'non-findings' are likely to occur. [THE THOUGHT IN THIS FOOTNOTE COULD BE PUSHED TO EMPIRICAL SECTION.]

[10] Specifically, the authors suggest that the impact of terrorism is "limited by the economic benefits of controlling that innate, emotional response."

[11] There are similar findings for this kind of behavior in response to environmental hazards such as Superfund sites. Depressed housing prices generally subside with time and return to their levels prior to the revelation of risk information (e.g., Dale et al. (1999; Gayer et al. (2000; Messer et al. (2006)).

[12] Browne and Hoyt (2000) finds that individuals' level of flood insurance coverage increases the number of flood occurrences the previous year(s), Kousky (2010) finds that homeowners in flood-prone areas may underinsure due to the infrequency of high-cost floods.

[13] CHECK that this the right characterization? Shafran (2011) performs a repeated-choice experiment with feedback where subjects can choose to self-protect from an unknown future loss. He finds more self-protection in response to a recent low-probability high-consequence event than for a recent high-probability event (suggesting a variant of a certainty/severity tradeoff).

revelation of the objective risk information of hurricanes relatively to tornadoes.[14] The increased lead-times for hurricanes allow individuals to consider the opportunity costs of relocating and preparing for an impending hurricane. There are larger opportunity costs on weekdays because relocation and preparation would have to occur during typical business hours and leads to greater measure of safety taken by individuals for hurricanes that occur on weekends. For tornadoes, there is not enough lead-time to consider a decision to temporarily relocate. The apparent over-riding effect on individuals increased safety on the weekdays for tornadoes is due to greater access of the protective building of one's place of employment than the relatively low quality structure of a typical home.[15]

NEED PARAGRAPH ON PROXIMITY EFFECTS

[MOVE THIS PARAGRAPH TO EMPIRICAL SECTION?]In contrast to these other studies, our research uses weekly observations on the demand for safe-room construction as evidenced by applications for construction rebates. These data allow us to detect changes in household behavior that may be apparent only at this finer time scale. Our analysis also explores the relationship between the spatial proximity of recent tornado events and the self-protection responses of homeowners. As noted in the hedonic literature (e.g. Bin et al. (2008); Hallstrom and Smith (2005)), the identification of spatial patterns in risk perceptions can be difficult when the level or location of the environmental threat is spatially correlated with other geographically heterogeneous amenities or disamenities that might also affect the economic response variable in question such as housing prices. Fortunately for our analysis, tornado paths are much more spatially random across a wide geographical region than many other threats, such as floods.[24] Our analysis also includes a large number of tornado events, so we are less likely to observe an incidental correlation between the location of one or two event paths and amenities.[25]

[14] CITE changes in forecasting of tornadoes.
[15] DOES ZAHRAN DISCUSS TORNAODES THAT OCCUR AT NIGHT?
[24] In comparison, flood risks identified by FEMA Flood Zone designations in the U.S. are spatially very specific.
[25] [MOVE THE SENTENCE OF THIS FOOTNOTE TO EMIPRICAL SECTION.] In our empirical models, we are also careful to include county-level fixed effects to sweep out the influence of any unobserved time-constant county-specific heterogeneity that may systematically affect safe-room installations in response to tornadoes.

Several states have enacted rebate programs to provide partial subsidies to homeowners and communities for the construction of safe-rooms in homes and other buildings, so our Arkansas data are merely an illustration. These Arkansas data have not been previously studied by economists. For the State of Oklahoma, however, Merrell et al. (2005) assess the net social benefits of a broad-based program to rebate the cost of safe-rooms for homeowners using Census data on the number of housing units in Oklahoma. These authors estimate the potential benefits in terms of reduced injuries and fatalities associated with a program that would pay the *full* costs of safe-room construction in all primary residences. They calculate that these costs would vastly exceed the expected benefits for safe-room installations at permanent homes, but net benefits would be marginally positive for the protection of occupants of mobile homes. In contrast, our goal is not to undertake a comprehensive benefit-cost analysis of a 100 percent subsidy to retrofit all homes. Instead, we seek to characterize temporal and spatial patterns in this particular type of extreme-weather-related adaptive behavior in the wake of tornadoes that occur both nearby and farther way, and to understand the potential policy implications for programs which may directly or indirectly incentivize this and other similar types of self-protection behavior.

3. Data

3.1. The Arkansas Safe-Room/Shelter Program

In recognition of the shelter-in-place option as a form of adaptation, this paper uses a unique dataset on applications for a subsidy for safe-room construction or installation in Arkansas between 2006 and 2010. Our data record the date of application for each rebate, which gives us a window on the approximate timing of household decisions to build these safe rooms and a way to understand the extent to which nearby tornado activity stimulates observed self-protection investments by households. For example, one might expect to see a small up-tick in safe-room construction shortly after a tornado, but that this effect may dissipate with the passage of time (at least until the next tornado). A tornado that is nearer to a household's primary residence may also result in a higher level of perceived risk for the homeowner.

Therefore, the closer the proximity of a tornado, *ceteris paribus*, the greater might be the effect on a homeowner's observed demand for new safe-room construction at their residence.

We use data on safe-room construction from the Arkansas Safe-Room/Shelter Program.[26] The Arkansas Department of Emergency Management (ADEM) administers the program, which provides rebates to homeowners for the construction or installation of a safe-room. To qualify for a rebate, safe-rooms must have been built (or come under contract) after January 21, 1999 at the homeowner's primary residence and they must meet the design criteria for "safe-rooms" outlined in the Federal Emergency Management Agency's (FEMA) publication 320 or the National Performance Criteria for Tornado Shelters standard.[27] FEMA characterizes their design criteria as providing "near-absolute protection" for individuals during weather events with extreme winds. This is in contrast to other construction standards which FEMA states as meeting only a basic requirement for protection. In addition to the FEMA criteria, eligible safe-rooms must also meet all state, city, and county codes. The rebates from ADEM cover 50% of the cost up to $1000. As of December 2011, more than $17 million has been distributed to over 17,500 Arkansas households since the program's inception in 1999.

Adequate safe-room rebate application data for our analysis are available from May 2006 to December 2010. During this period, a total of 6,637 safe-rooms were accorded rebates. The average annual number of applications for safe-room rebates, across all of the state's 75 counties, is roughly 1,400. The average number of applications per county varies considerably across counties. There is only one county which had no granted rebate within the time frame of our data. A valuable feature of the safe-room data is that they include the locations of safe-room installations to an exact street address. For our analysis, we aggregate weekly safe-room rebate requests spatially to the county level using the address of each homeowner's primary residence reported on the rebate application. Figure 1, however, shows the point locations of individual safe-rooms in Arkansas for which rebate requests were filed during our sample period. Figure 2 shows the state boundary for Arkansas, along with the polygons for individual

[26] We obtained these data through a Freedom of Information Act (FOIA) request.
[27] See FEMA publication 361, 2nd edition, August, 2008 and FEMA publication 320, 2nd edition, August, 2008.

counties and points for the geographic centroids of each county, overlaid by the approximate paths of all recorded tornadoes within 350 miles of any Arkansas county centroid from the beginning of 2005 through the end of 2010.

One drawback to the date reported in the rebate application is that it represents the date on which the application was processed by ADEM. It is not the date when the homeowner first decided to install a safe-room. The decision to install a safe-room will obviously predate the application for the rebate. We expect that the (unobserved) initial decision to install a safe-room may be precipitated by an elevation in perceived risk as a result of a nearby tornado. The earliest point at which the rebate may be sought is when the project first comes under contract. Thus there may be lags that stem from a shortage of contractors. Contractors for safe-rooms may be in short supply for more than one reason: (1) they may already have been engaged for other non-safe-room-related projects during the usual construction season, (2) they may already have committed to do other repair and rebuilding projects as a consequence of tornado damage in the same county or elsewhere, or (3) they may already be working on other safe-room installations in the same area.

Our lack of information about the exact date when a homeowner decides to invest in self-protection by installing a safe-room does not preclude our ability to draw conclusions about how the overall response of safe-room installation varies with the level of tornado activity or the distance of the tornado event from the homeowner's location. If the distribution of delay times (between the decision to install a safe-room and the time an application is processed at ADEM) is relatively stable, this reporting delay will only add noise to the process. The "time since tornado" will be measured with error and can be expected to produce some errors-in-variables attenuation in estimated coefficients. If we find statistically significant effects of elapsed time since a tornado on the number of rebate requests, we can anticipate that the real effects, in the absence of random heterogeneity in application delays, are probably at least as large as the estimated effects.

3.2. Tornado Events

The tornado events depicted in Figure 2 are derived from NOAA's National Weather Service (NWS). These data provide starting and ending coordinates for the paths of individual tornadoes. For each pair of coordinates, we approximate the tornado's path using a straight line between these two points. From the date of our first recorded safe-room rebate application in the last week of May in 2006, until December 2010, there were 186 recorded tornadoes in Arkansas. We also consider tornadoes beyond the border of Arkansas, to a distance of up to 150 miles, and tornadoes that occurred as early as the beginning of 2005, before the first recorded safe-room rebate application in 2006. This avoids truncation at the boundaries of space and time and permits the use of spatial and time-wise lagged tornadoes to explain safe-room rebate requests in each county in each time period. These extensions of the tornado sample result in a total of 1,462 tornadoes from which we construct our measures of tornado activity by interval of distance.

We construct spatial and time-wise measures of tornado activity related to each county using the NWS data on tornado events. We first develop a distance matrix that codes the minimum distance from each county centroid to every one of these 1,462 tornadoes. The tornado data include the date of occurrence of each tornado. In combination with the distance matrix, this allows us to construct measures of the presence of tornado activity within a given distance band relative to the centroid of each county in each time period. We choose weeks as the time-unit for our analysis and create weekly binary indicator variables for each county for the occurrence of any tornado activity within each distance range of a county's centroid. In our results section, we report estimates only for the set of weekly indicators for any occurrence of tornado activity within 0-50, 50-100, and 100-150 miles of a county's centroid.

Figure 3 shows the pattern of seasonality between January and December in the average number of safe-room rebate requests per county recorded by ADEM, as well as the average number of counties affected by tornadoes anywhere in Arkansas by week-of-year during the period from 2006 to 2010. The pattern depicted in the figure suggests that both tornado activity and safe-room rebate requests are most numerous during the early half of the year, roughly from early March (calendar week 10) to the end of June (calendar week 25), with rebate requests tending to trail tornado events during this part of the year. These simple multi-year averages of seasonal patterns in tornado frequency and safe-room rebate applications suggest that the relationship between these two variables can be clarified using regression-based methods.

4. Empirical Specifications

4.1. Basic Model

The time-period of our analysis is 240 weeks starting from the last week of May in 2006 and ending in December, 2010. The 75 counties in Arkansas yield a total of 18,000 county-week observations in our panel. Let S_{cw} be the total number of safe-room rebate requests recorded by ADEM for county c during week w. The number of rebate requests in a given county and week is a strictly non-negative integer, so for a majority of our regressions of the conditional mean of S_{cw} on a set of covariates X_{cw} we employ count data models.

Traditional regression models for count data include the standard Poisson (P) model, which constrains the conditional mean and variance of the count distribution to be equal, i.e., $E[S_{cw} \mid X_{cw}] = Var[S_{cw} \mid X_{cw}] = \eta_{cw}$. The negative binomial (NB) model relaxes the equality constraint between the mean and the variance and has a conditional mean and variance given instead by $E[S_{cw} \mid X_{cw}] = \eta_{cw}$ and $Var[S_{cw} \mid X_{cw}] = \eta_{cw} + v^{-1}\eta_{cw}^2$, where v (an additional parameter to be estimated) is a measure of the amount of dispersion in the errors. Many types of count data have some degree of overdispersion ($v > 0$). The overall marginal distribution for the number of safe-room rebate requests has a mean of .368 rebate requests and standard deviation of 1.1, suggesting that the conditional distribution, as a function of regressors, might also display a degree of overdispersion.

We specify a log-linear relationship for the NB conditional mean model of S_{cw}, of the form:

$$\log\left(E[S_{cw} \mid X_{cw}]\right) = \tau(T_{c,w-l}^{d}) + \mu_{woy} + \mu_{c} \qquad (1)$$

where $\tau(T_{c,w-l}^{d})$ is the temporal response portion of a county *c*'s (log) conditional mean number of safe-room applications. The temporal response in week *w* (where *w* indexes the week of the safe-room applications processed at ADEM) is allowed to be affected by the occurrence of tornado activity in the l^{th}

week prior to week w. The μ_{woy} are week-of-year indicators that we use as controls for unobserved variation in county-specific and seasonal factors that can affect the demand for safe-rooms. The μ_c are simple binary indicators for counties. For now, we include no other specific regressors. To start with, we adopt a non-parametric form for the temporal response function:

$$\tau(T^d_{c,w-l}) = \beta^d_{w+8}T^d_{c,w+8} + \ldots + \beta^d_0 T^d_{c,0} + \ldots + \beta^d_{w-40}T^d_{c,w-40} \, . \tag{2}$$

In this equation, the temporal response is specified by a linear and additively separable function of binary indicators, $T^d_{c,w-l}$, for "any tornado activity" the function includes eight weeks of leading activity and forty weeks of lagging activity. These binary variables take a value of one for any occurrence of a tornado in distance band d from the centroid of county c during the l^{th} week prior to week w and zero otherwise. The specification thus allows rebate requests to depend upon future, contemporaneous, and past tornado activity. We include future tornado activity indicators as a "falsification test," to permit us to check for the direction of causality. To economize on notation, we will omit the superscript d in what follows, except when necessary. The estimated coefficients β_{w-l} will reveal the temporal pattern of safe-room construction activity in response to recent and nearby tornado activity.

To contain the size of the parameter space, our actual implementation of the non-parametric model aggregates the weekly indicators into four-week sets (except for the contemporaneous week) such that

$$\tau(T_{c,w-l}) = \beta_{8/5}T_{c,8/5} + \beta_{4/1}T_{c,4/1} + \beta_0 T_{c,0} + \beta_{-1/-4}T_{c,-1/-4} + \ldots + \beta_{-37/-40}T_{c,-37/-40} \, . \tag{3}$$

For $T_{c,0}$, the measure of tornado activity is for tornadoes that occur during the same week as the processing of the safe-room applications. The variable $T_{c,-1/-4}$, for example, counts tornado events for the first through fourth weeks prior to the application processing week w. The other tornado activity indicator variables are analogous. We directly test the adequacy of the standard Poisson regression model by examining the statistical significance of the overdispersion parameter estimate in the results for the NB model. We also compare the estimates of the temporal lag coefficients of the NB model to those of

Poisson model. Finally, we compare these estimates to corresponding estimates obtained via ordinary least squares.[28,29] w Given the size of the geographic region we consider in our analysis, it is not uncommon for multiple tornadoes to occur in the course of a week (and in some cases on the same day) within a given distance buffer around the centroid of a given county. For this reason, we present additional models which simultaneously control for tornado activity between 50 and 100 miles (d=100), and between 100 and 150 miles (d=150) of a county's centroid over the same time periods. This generalization helps preclude omitted variables bias that may be present when modeling the temporal response function only for the closest distance band (of 0-50 miles). This richer model also allows us to examine explicitly the dependence of self-protection activity on the spatial proximity of tornadoes.

We control for time-wise heterogeneity shared across all counties by including indicators for each month of the year, μ_{moy}. As in many parts of the country, peak season for housing construction in Arkansas starts in spring and continues until fall. This annual cycle for construction coincides closely with the season for peak tornado activity in Arkansas. Without including μ_{moy}, there would be potential upward bias in the magnitude of the temporal coefficients in (1).[30] In addition, topography may systematically affect expected tornado frequencies and may thus mediate individuals' perceived risk of tornado activity. Likewise, differences in average income levels across counties will affect the expected number of safe-room rebate applications. Rather than trying to quantify all the possible relevant time-

[28] Coefficient estimates in Table 1 were obtained with pre-packaged commands in Stata 11.

[29] Of the three distance ranges from a particular county centroid that we consider for a given tornado to possibly enter, only the closest "affected" range is registered by the binary tornado activity indicator. The activity indicators for all other distance bands for that county would be coded as zero unless there happen to be another nearby tornado in the same week. Thus, we essentially make the assumption that homeowner behavior with regard to self-protection is determined by their "nearest point of contact" to a given tornado. For example, the tornado activity indicator $T^{50}_{c,w-0}$ takes on a value of one if there is any tornado path whose closest point is within 50 miles of the centroid of county c for safe-room rebate requests that are contemporaneous with the week of the tornado occurrence. We initially generate separate estimates of specification (3) for tornado activity in the distance band from 0 to 50 miles (d=50) of a county's geographic centroid.

[30] In an earlier working paper, we considered the use of 52 weekly time fixed effects. We found that the overall temporal response is minimally sensitive to the use of the weekly versus monthly fixed effects.

invariant factors, specification (1) includes county fixed-effects μ_c as controls for any unobserved county-level heterogeneity that is constant between 2006 and 2010.

In the Appendix, we discuss alternative count models such as the conditional fixed-effects negative binomial (FENB) estimator (Hausman et al. (1984)), the zero-inflated negative binomial (ZINB) estimator, and a NB specification that includes yearly indicator variables for the five calendar years of our data. The results from the FENB and ZINB specifications provide estimates of the lag coefficients that are very similar to those for the NB. The magnitude of the peak percent change in safe-room demand in response to a tornado occurrence, based on the NB specification that includes year fixed effects, is about half the peak response produced by the NB specification without year fixed effects. [31]

4.2. A More-Parsimonious Parametric Specification for the Temporal Response Function

Use of the full set of leading and lagging indicators for tornado occurrences in the specification of $\tau(\cdot)$ in equation (2) allows for a highly flexible time pattern in safe-room rebate applications in response to recent tornadoes. However, we would prefer to represent the temporal response of self-protection more parsimoniously, using a smooth functional form defined over the elapsed time since tornado events. Distributed lag models are a traditional method for estimating smooth temporal functions of an outcome variable in response to a time-denominated regressor (e.g., see Zellner and Geisel (1970) and Davidson and MacKinnon (2009)). A smooth lag function reduces the dimensionality of the parameter space and can considerably alleviate the burden of identifying individually statistically significant time effects among a large set of lag indicators, often without much loss of fit.

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[31] We attribute this to the yearly variation in tornado activity found in our data. Of the 186 recorded tornadoes in Arkansas, only a single F4 tornado (on the Fujita scale (F0-F5) for tornado intensity) is recorded during the time period of our analysis. This tornado occurred in early February of 2008 and caused 13 fatalities and 139 injuries. There are no F5 tornado occurrences during this period. Thus, our results in Tables 1 – 3, which do not include year indicator variables, are best interpreted as capturing the average tornado intensity effects that occurred during the time period.

We smooth our temporal response by constraining the coefficients in equation (2) to vary across lags according to a function that mimics the basic shape of a two-parameter gamma distribution, which takes the general form:

$$h(l;\lambda,\phi) = l^{\lambda-1}\frac{\exp(-l/\phi)}{\Gamma(\lambda)\phi^{\lambda}}, \tag{4}$$

where λ is a shape parameter, and ϕ is a scale parameter. When $\lambda = 1$, the gamma distribution becomes an exponential distribution with a value for the decay rate of $1/\phi$.[32]

The domain of the gamma distribution is non-negative, so we restrict our models to include only contemporaneous and lagged tornado activity, i.e. $l \geq 0$.[33] We scale the overall height of $h(\cdot)$ by a third parameter β to obtain the systematically varying lag coefficient β_l (i.e., $\beta_l = \beta h(l;\lambda,\phi)$). This structure for the lag coefficients allows first for an increasing, then a decreasing, effect of lagged tornado activity on safe-room rebate requests.

With this relatively flexible gamma-distribution form for the lag coefficients, the log-conditional mean of the NB count model is:

$$\log\left(E[S_{cw}]\right) = \beta_{50}\left[\sum_{l=0}^{40} h(l;\lambda_{50},\phi_{50})T^{50}_{c,w-l}\right] + \mu_c + \mu_{moy}, \tag{5}$$

where $h(\cdot)$ is the same across for each county *c* and week *w*. In specification (5), the subscripts on λ, ϕ, and β indicate that these coefficients are relevant for tornado activity that occurs within 0 to 50 miles of each county centroid. Similar to our non-parametric models, we then also estimate the differentiated effects for tornado activity in the *two* nearest bands to county centroids (i.e., 0-50 and 50-100 miles in

[32] This is merely a richer alternative to the widely used geometrically declining lag structure. The use of lag functions in the shape of a gamma distribution was first suggested by Tsurumi (1971) and Schmidt (1974).

[33] With this assumption we sacrifice our ability to model rebate requests as a function of future tornadoes. This should not be a major concern since tornado activity in future periods should have no systematic effect on current period shelter installations. In Figure 4, of course, our results show that the estimated leading coefficients in the non-parametric model in specification (3) fail to reject the assumption of a zero effects on rebate requests of future tornado events.

proximity) and then for each of *three* bands. For the specification with all three bands, the parametric model is:

$$\log\left(E[S_{cw}]\right)=\sum_{l=0}^{40}\ [\beta_{50}h(l;\lambda_{50},\phi_{50})T^{50}_{c,w-l}+\beta_{100}h(l;\lambda_{100},\phi_{100})T^{100}_{c,w-l}+\beta_{150}h(l;\lambda_{150},\phi_{150})T^{150}_{c,w-l}]$$
$$\ldots+\mu_c+\mu_{moy}, \tag{6}$$

where the number of parameters to be estimated is reduced to just nine (from potentially 120 in a specification that uses the non-parametric temporal response function in (2)).[34] Finally, in an illustration that uses just the 50-mile distance band, we allow each of λ_{50}, ϕ_{50}, and β_{50} in specification (5) to vary systematically with both median household income (*income*) and the percent of individuals with some college experience (*education*). County-level information on income and education come from the year 2000 U.S. Census.[35]

In the discussion of our findings, we will report the six additional estimated coefficients (i.e. the three pairs) related to county-level income and education levels and then illustrate the overall effects of these household characteristics on the magnitude of peak demand and the elapsed time until the peak in safe-room rebate requests. We can calculate the individual effects of income and education predicted by our model, *ceteris paribus*, by using the fact that the location of the mode of a gamma-type function (i.e., elapsed time until peak applications) for our basic two-parameter distribution is given by $(\lambda-1)\phi$ for a shape parameter of $\lambda\geq 1$, which is independent of the height of the function as measured by β. To calculate the magnitude of the peak estimated change in safe-room rebate requests after a tornado, we simply allow l in the temporal response function $h(\cdot)$ to be the calculated mode and predict the percent

[34] The nonlinear form of the lag structure in our models with specifications similar to (5) and (6) precludes the use of convenient pre-programmed estimators. We programmed the specialized log-likelihood for our estimators using the *ml* routine in Stata 11.
[35] The strongest household response is likely to appear for tornado occurrences within the range of 0-50 miles. This distance band is likely to provide the clearest empirically estimated effects of income and education. It is much harder to identify distinct income and education effects simultaneously on all nine of the time profile parameters in equation (6) if each is simultaneously generalized to a systematically varying parameter that is influenced by both current income and current education levels in the county in question.

change in peak demand at simulated values for λ and ϕ over specified observed values of income and education.

5. Findings

5.1. Non-Parametric Temporal Response for Tornado Activity within 50 Miles

The parameter estimates in Table 1 are for the non-parametric form in specification (3). The individually estimated lag coefficients represent the average percent change in the number of safe-room rebate requests as a consequence of future, concurrent, and past tornado activity within fifty miles of each county's centroid in a given week. In these models, we control for seasonal effects with monthly indicators and allow for thirteen individually estimated lag and lead coefficients. Coefficients represent the average percent change in the number of safe-room rebate requests for a change in the respective independent variable.

For the conditional fixed effects linear estimator in Model 1, the average effect of tornado activity on safe-room rebate requests is indistinguishable from zero in the week of the tornado event and up until the fourth week after an event. Safe-room rebate requests begin to reflect increased subjective tornado risks at a point roughly one month after the precipitating tornado event. The predicted average effect on safe-room rebate applications, according to Model 1, reaches a maximum of 68.9 percent above normal for the number of safe-room rebate requests between nine and twelve weeks after a nearby tornado event.[36] After this surge in applications, household demand returns to pre-event levels within about nine

[36] We obtain the coefficients in Model 1 by scaling the dependent variable by .3687, the mean number of weekly rebate requests per county over the entire time period. The log transformation of the number of shelter rebate requests, along with adding 1 to the number of shelter rebate requests before transforming, are two other possible scaling alternatives to obtain percentage change effects. In both cases, we find that the analyses based on these alternative transformations have drawbacks. Since the simple log transformation is undefined at zero, its use limits our sample to only those 3,461 observations for which the number of shelter rebate requests in a county is nonzero. For the shifted log transformation, the presence of a disproportionate share of county-weeks with zero rebate requests biases downward the temporal lag estimates. The alternative count-data models featured in Table 1 (and Appendix Table A1, which includes the zero-inflated models) more appropriately treat the number of rebate requests as a non-negative integer. They allow us to model the temporal effects of nearby tornado activity while also including disproportionate numbers of county-week observations with zero rebate requests.

months (i.e., 36 weeks) after a tornado occurrence. Model 1 also includes a full set of seasonal indicator variables for each week of the year. In another model without the monthly indicators (not reported), we find a shorter delay in the increase in safe-room rebate requests after an event. The monthly indicators thus appear to control for seasonal correlation between tornado activity and unobserved time-wise heterogeneity in the market for safe-room construction (such as general levels of construction activity and the availability of contracting resources over the course of a year).

We assess the robustness of the results from the log-linear regression in Model 1 of Table 1 against Poisson and standard NB count models in Model 2 and Model 3. These count-data models allow the log of the expected value of the number of safe-room rebate requests in a given county-week to vary according to the same set of regressors used in Model 1. Both the Poisson and NB models have lag coefficients that are noticeably smaller in absolute value, which is to be expected because the dependent variable in Models 2 and 3 is implicitly logged. The positive and statistically significant dispersion parameter in Model 3 suggests the presence of overdispersion even after conditioning on the leads and lags of tornado activity and the other covariates. Overdispersion not captured by the Poisson model may thus explain Model 2's statistically negative effects on rebate requests for concurrent week tornado activity, as well as the apparent decrement in applications during weeks 37 through 40.

However, it is not implausible that there could be a negative differential in safe-room rebate requests in the week corresponding to a nearby tornado. Subsidy applications might fall off because of the distraction of a local tornado, and many non-specialized local contractors may be busy responding to the demand for emergency repairs due to local tornado damage. Contractors would be less available for "preventive" projects such as safe-room installations and, thus, there could be delays in the negotiations of the contracts required before safe-room rebate applications can be processed. In the immediate aftermath of a tornado, the most directly affected households may also be taking care of their own needs or the needs of their neighbors or their community, and thus do not have the time to complete the rebate application process, so that demand falls below normal levels. It may also be the case that the types of storms which produce tornadoes coincide with weather and soil conditions that are unfavorable for the planning or excavation/construction of outdoor in-ground safe-rooms.

The substantial post-tornado up-tick in safe-room rebate requests revealed in Table 1 (peaking at 9-12 weeks and returning to the long-run steady-state by about 37-40 weeks after a nearby tornado) is considerably more short-term than the yearly temporal adjustment process found in the existing literature for the effects of hurricanes and floods on post-disaster insurance take-up and housing prices (e.g., Gallagher (2010)). Furthermore, despite the fact that safe-room supply constraints may bind differently over time, the overall temporal response of households suggests that average risk perceptions of households vary with elapsed time since recent nearby tornado events. The eventual decline in the demand for safe-room rebates with increasing time since the last tornado event could be evidence for the underlying influence of availability bias in household behavior, where a spike in demand for self-protection appears to decay over time, due either to an increasing tendency to forget, or to the dissipation of fear/anxiety about similar future events.

5.2. Differences in the Temporal Response Function across Distance Bands

The left-hand panel of Figure 4 shows the estimated individual lag coefficients (with confidence intervals) based on Model 3 in Table 1 for tornado paths that come *within 50 miles* of each county centroid. The right-hand panel of Figure 4 shows the analogous coefficients when we separately estimate a model that uses indicators for tornado paths that pass *between 50 and 100 miles* of each county's centroid. There is a significant decrease in the strength of the response as the distance of the tornado activity increases from 0-50 miles to 50-100 miles.

The effects for the two distance bands shown in Figure 4 are not produced by a single model, so omitted variables bias may afflict the estimated coefficients in each case. Including multiple sets of these thirteen lead/lag coefficients in an expanded non-parametric model, however, can reduce the precision of the distinct lag-coefficient estimates due to the potential correlation of tornado activity across distance bands. Instead, the parametric models in Table 2 (based upon a flexible but systematic gamma-distribution pattern for the lag coefficients) show the same reduction in the effects on household safe-room demand as we consider tornado activity that is farther away.[37]

In Model 1 of Table 2, we model only tornado activity within 50 miles of each county centroid based on specification (5). The results show that all three parameters, ϕ, λ, and β of the gamma-distribution form of the temporal response are statistically significantly different from zero. The other columns of Table 2 shows the parameter estimates for the analogous parametric lag structure in specification (6) when we expand the specification to simultaneously model tornado activity between 0-50 and 50-100 miles (Model 2), and then for 0-50, 50-100, and 100-150 miles of each county centroid (Model 3). In comparison to Model 1, the estimate for overall scale parameter, β, for the 0-50 lag coefficient function of the temporal response declines across Models 2 and 3 (as well as across distance bands within Models 2 and 3). This suggests that the single-band estimate in Model 1 of the overall scale of the response of safe-room rebate requests to tornado activity within 0-50 miles of county centroids (i.e. the β in Model 1 of Table 2) partially reflects correlated tornado activity within the other distance bands farther away.[38] As apparent in Models 2 and 3, the overall scale of the response to tornado activity between 50-100 miles of county centroids is about one-third the size of the overall scale for activity between 0-50 miles. Model 3 indicates that by the time we consider tornado activity between 100-150 miles of each county centroid, the parameter for the overall scale of response, β, is the only one of the three gamma-distribution parameters that has any role in explaining safe-room rebate requests.

Although the estimates of ϕ and λ in Model 3 of Table 2 are insignificant for the 100-150 mile distance band, all three parameters of the temporal response are highly significant for the other two closer distance bands. For Model 3 in Table 2, Figure 5 displays the estimated lags for the gamma-shaped temporal response function (along with 95% confidence intervals) for the 0-50 and 50-100 distance bands. For tornado activity within 50 miles of each county's centroid, estimated peak safe-room rebate

[37] The Models in Table 2 also include controls for county fixed effects and month-of-year effects.
[38] Such correlated activity could result from a single storm that produces multiple tornadoes over a short period of time within a region.

requests represent roughly a 20% increase at about 13 weeks after a tornado. When the tornado activity is between 50 and 100 miles away, however, the size of the peak response of applications is reduced to less than 10%, and this peak appears to occur in the first couple of weeks after the tornado event (perhaps because contractors are less likely to be fully booked at these distances). The results from the simultaneously parametric model thus confirm the results suggested by the separate non-parametric models for each distance band: in addition to the elapsed time since the last tornado occurrence, a household's proximity to a recently affected area also appears to be a factor in the formulation of risk perceptions and subsequent demand for safe-rooms.

5.3. Income and Education Effects

The results discussed in the previous section indicate that the overall magnitude of household response is at least partially determined by a household's temporal and spatial proximity to a tornado occurrence. Systematic differences in subjective tornado risks might be captured by county income levels (to represent the value of the housing assets at risk and the opportunity cost of time lost to injury), and by education levels (as a proxy for comprehension of probability concepts). For the 0-50 mile distance band, Table 3 shows the estimated effects of education and income when we permit both of these variables to shift each of three parameters of the gamma-distribution form of the temporal response function. County median household income and the percent of individuals with college experience have no effect on the overall amplitude of the lag coefficients, β, but they do both affect the shape and scale parameters, λ and ϕ, of the gamma distributed form of the temporal response function.

These income and education variables enter the nonlinear gamma-distribution function in more than one place, so it is difficult to summarize the overall marginal impact of either variable on the temporal response pattern in safe-room rebate requests based only on the estimates shown in Table 3. To provide a clearer summary, we explore in Figure 5 how the height of the peak response, and the timing of this peak, change as we hold one variable constant at its sample mean value and adjust the other variable across the range of its observed values in our county-level data. Specifically, we calculate the predicted timing of peak applications, $(\lambda - 1)\phi$, and the percent difference in the height of the function at this mode (which will also involve the β parameter). Figure 6 shows how each of these two features of the fitted lag structure changes in response to independent variations in income and education.

Specifically, Panel A of Figure 6 shows that counties with higher incomes tend to exhibit a higher peak in safe-room rebate requests than counties with lower incomes, holding the education variable constant.[39] Panel B shows the effect of income on the timing of peak applications, and suggests that peak applications are reached somewhat sooner both in low-income and in high-income counties, compared to medium-income counties. Thus, high-income households are likely more willing to pay a premium for a safe-room than low-income counties (suggesting that observed self-protection patterns for higher-income households may be more volatile if demand is prompted by a strong yet short-lived fear response). High-income households would also be more willing to pay a premium to recruit an out-of-area contractor to speed up their safe-room installation process. Given that lower-income areas exhibit a shorter-duration response to tornadoes (as implied by Panel B), short-run supply constraints may be less binding in lower-income areas, so that a contractor can be identified, and a contract drawn up, more quickly.

Panels C and D of Figure 6 show the effect on safe-room rebate requests of differences in education (i.e. the percent of individuals in a county with any college experience). In Panel A, the predicted magnitude of peak demand drops quickly as education is greater, holding household income constant at its observed mean value. This may capture the effect of education on subjectively formulated risks—individuals with more education appear less likely to over-react because they are more capable to assess accurately the objective probability of a future adverse event. As was the case for differences in

[39] The correlation between the income and education variables is 0.742. Thus, in the observed data, an increase in income (which raises the height of peak applications) would be offset by an increase in educational attainment (which decreases the height of peak applications). If, on the other hand, there is a negative or positive income shock to a county or set of counties without a corresponding change in education levels (as might be the case with the recent payments made to residents in some counties in Arkansas by natural gas companies for exploration and leasing rights), our results provide an indication of the expected change in safe-room rebate requests that would occur as a result.

income, however, the timing of peak applications first increases with education and then decreases. Higher levels of education may make it easier for homeowners to track down an available out-of-area safe-room contractor, accounting for the earlier peak in more highly educated communities. There may be more available contractors and laborers per household in areas with lower levels of college attendance, which could account for earlier peak applications in these communities.

5.4. Price Sensitivity

If markets for safe-room installations are somewhat localized, so that suppliers have market power, contractors may be quick to increase their prices in response to sharp increases in demand after a tornado. Price discrimination is certainly possible in the market for custom-installed equipment like safe-rooms, since resale opportunities for just a safe-room by itself are certainly limited by the cost of removal and relocation, if resale is feasible at all. If short-run demand becomes much less price-elastic in the wake of a nearby tornado, contractors may profit-maximize by differentiating their prices over time as demand conditions vary. Homeowners might also demand shelters with more premium safety features after a recent and nearby tornado. All of these factors lead us to hypothesize that the prices of safe-rooms should be higher after a tornado.

The lags between tornado events and the peak number of ensuing safe-room rebate applications could also be explained in part by a reluctance of many homeowners to pay inflated prices when supplies are most severely constrained. Homeowners may continue to shop around, or to wait until their preferred contractor has an opportunity to bid for the job and draw up a contract, or they may give up looking for a contractor and install a safe-room themselves if they have the skills to do so.

To investigate the possibility of short-term changes in safe-room prices after a tornado occurrence, it would be highly desirable to have actual safe-room installation expenditures for each household that applied for a safe-room rebate. Unfortunately, installation costs in our data are heavily censored. The official records include only the *rebate* amount the applicant received, which is 50% of the installation costs up to $1000. There is only a very small share (i.e. 10%) of applications for which reported safe-room installation costs are not top-censored. For top-censored data, however, it is still possible to use a random effects top-censored Tobit regression model to attempt to obtain estimates of the effects of recent nearby tornado activity on safe-room expenditures.

In results reported in Appendix Table A2, we use this Tobit-type estimator to explain these heavily censored safe-room installation costs using the same set of explanatory variables employed in Model 1 of Table 1. In this case, however, the censoring is so extreme that the estimated lag coefficients for tornadoes in the 0-50 miles distance band do not seem to follow any distinguishable pattern. In our preferred specification (which includes year indicators and adjusts costs for inflation), we find statistically significant effects for only two of the lag coefficients (for weeks 1 through 4, and weeks 17 through 20). The signs on these two lag coefficients are also negative, which runs counter to our hypothesis at supply constraints after a tornado should result in price increases. The point estimates for the other lag coefficients vary widely in size and sign. Thus, based on these extremely censored price data alone, there does not seem to be sufficient evidence to support the conjecture that equilibrium prices for safe-room installations are bid up substantially after nearby tornado events. We must look for other indications.

5.5. Direct Evidence for Supply Constraints

Supply constraints may also be acting in such way as to lead to other differences in the observed response of household demand for safe rooms. As an indication of this possibility, Figure 5 also shows that the estimated timing of peak rebate requests is earlier by roughly ten weeks if the tornado activity occurs at 50-100 miles from a county's centroid, rather than within 50 miles of its centroid. The short-run supply of local contractor time is likely to be less binding at greater distances from actual tornado activity. Short-run labor supply constraints could be more binding if there is greater demand for construction labor to repair to damaged buildings or homes closer to the vicinity of the tornado event. Competing demands for safe-rooms in closer proximity to recent tornado strikes may also cause delays. For those households which are farther away from a damaged area, the absence of these factors could mean shorter delays in the arrangement of individual safe-room construction contracts.

We look for direct evidence of the evidence of binding supply constraints using a separate dataset. The ADEM began collecting the names of the contractors associated with safe-room construction or installation in the last week of July 2008. Although the addresses of these contractors were not recorded in the application materials, we were able to track down street addresses and zip codes for 2,634 of the 3,401 applications processed by ADEM between late July of 2008 until the end of December 2010, where the end of this sample corresponds to the most recent information about tornadoes in the SHELDUS data set.[40] We geocoded the zip codes of each contractor for which an address could be identified, and joined the locations of zip code centroids to each of the 75 counties in Arkansas. We similarly geocoded the zip codes of the home addresses where safe-rooms were installed. This allowed us to measure the distance, in miles, between the zip code centroids for each job site and the business address of the contractor involved in the project.[41]

Based on the SHELDUS tornado data concerning individual tornado events indexed by county, we aggregated the information on tornadoes to the level of the county and the week (measured since January 1, 1960). We calculated the number of tornadoes in each county/week, the number of tornado-related injuries and tornado-related fatalities, as well as the measure of total property damage. We then constructed 15 weekly lags of the variables available for tornadoes and linked all of this tornado information to each safe-room application (according to the county and the week of the application). We also calculated a measure of total tornadoes across all counties in Arkansas, with 15 weekly lags of this variable as well.

The spatial distribution of houses and the corresponding spatial distribution of safe-room contractors will dictate the average distance to all available contractors for each house. This can be expected to vary across counties, so any model to explain "distance to contractor used" as a function of recent and nearby tornado activity must employ county-level fixed effects. We also employ weekly fixed

[40] The Spatial Hazard Events and Losses Database for the United States, described at http://webra.cas.sc.edu/hvri/products/sheldus.aspx

[41] Only the names of contractors were collected in the safe-room applications database. It was necessary to search elsewhere (laboriously, mostly via the web pages of each business) for address information for each contractor.

effects to control for ordinary seasonality in the contracting industry. In these data, however, our 15-week lags reach back to capture two particularly bad weeks in the early spring of 2008 where a total of 40 tornadoes struck in Arkansas. In contrast, only 25 additional tornadoes struck the state between the end of July 2008, when our safe-room application data with contractor addresses starts, and the end of December 2010.[42]

Table 4 reports selected lag coefficients from three different models, each of which seeks to explain a different indicator of supply constraints in the market for safe-room installations. Each model includes current-week own-county tornado events as well as 15 weekly lags of this number of events. Any coefficient on these current or lagged tornado event variables is statistically insignificantly different from zero if it is not reported in Table 4. Model 1 reveals that it seems to take eight weeks for a tornado in the same county to have any statistically significant effect on average contractor distances, at which time the average distance is greater by 8.7 miles. Recall that Table 1 reveals that safe-room rebate requests do not tend to become strongly statistically significantly different from normal until five to eight weeks after there has been tornado activity within a 50-mile radius of the county centroid. It seems reasonable that, as homeowners jockey for space in contractors' schedules during this increase in demand, they will have to range further afield to find a contractor.[43]

People may also be more likely to install a safe-room themselves, without the help of a contractor, if the supply of contractors is tight. Model 2 in Table 4 reveals that the only statistically significant difference in the propensity for homeowners to self-install their safe-room is positive, although small, and it occurs at a point eleven weeks after a tornado in the same county. The eventual decision to

[42] We opt to exclude the severe rash of tornadoes in the early spring of 2008 by beginning our panel more than 15 weeks after those events. Those 40 tornados were sufficiently unusual to imply a different data-generating process. A total of 73 tornados were recorded in Arkansas during the periods reflected in our analysis (weeks 2,515 to 2,651, counting from January 1, 1960).
[43] The sparseness of rebate applications in the weeks immediately following a tornado is not surprising. Certainly, in the week after the rash of tornadoes in early 2008, only eight safe-room applications across the whole state were recorded at the ADEM.

self-install a safe-room may be a consequence of an inability to identify an available contractor during the immediate weeks after a tornado event.[44]

Finally, homeowners may use high-volume experienced safe-room contractors when the market is slack. However, they may resort to smaller non-specialist or less-experienced contractors when the market it tight. For non-specialist and infrequently used contractors, we assume we are less likely to be able to track down an address and zip code for the contractor in question. About 22% of the contractors in our sample of safe-room applications fall into this "obscure contractor" category. Model 3 in Table 4 reveals that for safe-room rebate applications that are processed one week after a tornado in the same county, there is a statistically significantly greater chance that an obscure contractor will be involved. This suggests that if a homeowner wants a safe-room in a big hurry after a tornado, he or she may be happy with whatever contractor can be found on short notice, even if the contractor in question may not be equipped to provide the price and quality advantages associated with specialization, experience, and economies of scale.

One final set of analyses using this later sample of safe-room rebate requests (for which contractor information is available) focuses on distance to the contractor as the dependent variable. The models for which selected coefficients are reported in Table 5 rotate through a selection of alternative tornado metrics in addition to simple counts of tornado events. Models 2 and 3 in Table 5 reflect the intuition that own-county tornadoes that result in more injuries or more deaths are likely to result in homeowners going farther afield (i.e. incurring greater costs) to find an available contractor. The evidence suggests that homeowners who submit safe-room rebate requests the soonest after an own-county tornado has caused injuries or fatalities use contractors an average of 24 miles farther away per tornado injury in their county in the third week after these injuries. By week eight, however, the extra distance per injury has shrunk to only about three miles. While there are few fatalities in these data, a tornado fatality adds 33 miles to contractor distance by the eighth week after that fatality. By the eleventh week after own-county

[44] If they self-install their safe-room, rebate applicants can claim the subsidy only for materials, not labor.

tornado injuries or fatalities, however, average distance to contractors is statistically significantly lower than usual. Perhaps households with the most urgent demands for safe-rooms in response to injuries or fatalities have by that time engaged their contractors and submitted their rebate requests.

The final model in Table 5, for the effects of lagged own-county property damage from tornadoes suggests the possibility of a second wave in contractor demand, perhaps due to two latent classes among homeowners. At week 3, distances to contractors are as much as 20 miles greater per million dollars in own-county tornado damage, but they shrink by week 8 and become even slightly less than average by eleven weeks after an event. However, there is a significant increase in average distances again at week 15. Of course, some caution must be used in interpreting these results because there are relatively few events over the short time-span of the data for which contractor names are known so that distances, self-installation, or obscurity of contractors can be determined.

The results in Tables 4 and 5, taken together, constitute evidence for (a.) greater, rather than lesser, distances from the job site to the contractor's location, (b.) increases (rather than decreases) in decisions to self-install a safe-room, and (c.) the greater (rather than lesser) use of obscure contractors immediately after a nearby tornado. On the whole, these findings suggest that the supply side for safe-rooms may represent a discernibly binding constraint in the wake of tornadoes. This supports our contention that prices of safe-rooms, though mostly unobserved, are likely to be driven up after each tornado strike. This means that some portion of the safe-room subsidy is merely passed through to contractors, or stimulates additional demand to an extent that homeowners resort to less experienced or non-specialist suppliers and may therefore get less quality for their money.

6. Discussion and Conclusions

Our findings suggest that individuals' adaptive behavior in response to tornadoes—and thus likely to other extreme weather risks or intermittent natural hazards such as earthquakes—are mediated both by the elapsed time since the event and by distance from the event. We estimate a time pattern in applications for safe-room rebates that reaches a maximum at about 10 weeks after a tornado occurrence within a distance of 50 miles. Peak safe-room rebate requests increase with income and decrease with education levels. The up-tick in safe-room rebate requests remains statistically greater than zero for 36 weeks (about 9 months). For tornadoes that occur farther away (>50 miles), peak rebate requests appear to occur sooner suggesting that short-run supply constraints may be less binding at greater distances from a recent tornado.

The "half-life" of elevated risk perceptions over time and space appears to be an important determinant of the extent to which individuals can be expected to self-protect when they live in an area that exposes them to extreme weather events. The overall response of self- protection from tornadoes, however, may not be warranted by any changes in the actual *objective* risks of tornadoes. The forthcoming IPCC report on the current and likely future characteristics of extreme weather specifically notes that there is little if any statistical evidence for changes in local tornado activity since 1950.[45] Observed aggregate safe-room demand appears to reflect finer patterns of temporarily heightened and relatively localized subjective perceptions of tornado risks. The salience of these risks will vary over time and space because individuals' fear/anxiety and recollections of tornadoes may decline over time and with the geographical distance from affected areas. Fortunately, however, safe-room installations represent more-or-less permanent changes to the stock of housing capital in a region. While the salience of tornado risks may fade when there has been no recent tornado nearby, the safe-rooms remain. Each tornado may serve to "ratchet" upwards the percent of dwellings with safe-rooms, although conceivably by a decreasing amount because the proportion of unprotected dwellings will decline over time.

The variation in safe-room demand over time as a function of the location of tornadoes presents a challenge for policy makers, especially given the current uncertainty of the IPCC about trends in the objective risks of tornadoes and other extreme weather events. Policy makers may decide that individuals are providing *insufficient* self-protection because of the decline in households' perceived risks over time and across space. In this case, our results provide some clues as to how policy improvements might be

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[45] The report does not, however, entirely preclude the possibility for some future change. The IPCC's "low confidence" in possible future trends in tornado activity is largely attributed to the inadequacy of monitoring systems and variations in the quality of historical data on tornadoes.

made. Policies that encourage private investment for adaption but ignore the temporal and spatial nature of individuals' behavioral response may be able to achieve greater levels of economic efficiency by targeting incentives towards households according to whether an area has, or has not, been recently exposed to a nearby hazardous event. This might entail that rebate programs accommodate the presence of supply constraints by adjusting incentives over time and space as a form of "peak load" management to reduce costs. In the extreme case where few additional qualified contractors are available and the marginal cost curve is nearly vertical, the urge to take self-protective action may dissipate before supply catches up to demand.

The temporal and spatial targeting of safe-room installation incentives of course does not mean that less public assistance would be given to areas that have actually suffered damage from extreme weather events. Instead, it simply means that homeowners in the vicinity of a recent tornado may require much less in the way of a publicly funded subsidy to be encouraged to engage in an appropriate amount of self-protection. Homeowners in other areas—that may have comparable long-term risks but have escaped any recent or nearby damage from extreme weather events—may need more subsidization to undertake an appropriate amount of self-protection. If these types of homeowners can be induced to undertake safe-room installations during a lull in nearby tornado activity, local safe-room contractors could remain more fully employed. This type of "load management" would also help to reduce the apparent spikes in installation costs in the wake of a nearby tornado.

Policy makers may also decide that individuals desire too much self-protection relative to the level of concern warranted by any actual changes in the objective risks of extreme weather. In a related discussion, Sunstein and Zeckhauser (2011) suggest the potential need for a government to "not swiftly capitulate" to demands for public protection in cases where individuals appear to overreact to fearsome risks, such as to potential flooding or environmental threats. In the case of private investments, the self-limiting effects of the market, such as higher prices in response to heightened demand, can slow unwarranted protection investments if short-run and long-run supply constraints are present. Thus, a government may decline to provide public protection for extreme weather risks. However, if private demand for investments in self-protection is sufficiently strong, there may still be public support for well-targeted incentive programs. This can be the case even if an individual's subjective risk perception matches the long-run objective risks of extreme weather. Recent exposure to an event like a tornado may still not be sufficient to overcome other overriding deterrents to action, such as inappropriately high individual discount rates, or binding income constraints combined with imperfect capital markets.

The lack of high-quality price data for each safe-room installation limits our ability to draw causal inferences from our findings. Price data would be ideal because these would provide the clearest way to identify the temporal and spatial adjustment effects of imperfectly elastic supply for safe-room installation in the wake of a recent and nearby tornado. As a further prospective generalization of our analysis of supply constraints, it may be possible to acquire data on housing starts in each county, by month (or even by week) based on other types of permit applications. This may be a reasonable proxy for the amount of slackness in the construction industry in each county in each time period.

The heavy censoring of installation costs also restricts our ability to estimate bounds on the willingness to pay (WTP) for the perceived reductions in injury and mortality risks from tornado activity. An understanding of Arkansas homeowners' WTP for these protective measures could be used to evaluate the effectiveness of the Safe Shelter Program in increasing the level of self-protection undertaken and the degree to which the effectiveness of the program diminishes with elapsed time and distance from a tornado occurrence. Furthermore, expenditures for self-protection would be just one crude measure of the potential losses in social welfare if the overall frequency of severe weather events increases or if the geographic footprint of severe weather widens or shifts. If the need for adaptive behavior could be reduced by climate change mitigation measures, these avoided costs could be counted as one component of the "social cost of carbon." The broader economic impacts of extreme weather may also go well beyond just repair and rebuilding of structures directly damaged. Greater perceived risks from tornadoes and other extreme weather events may spawn numerous new demands for methods of self-protection over a much wider area and lead to growth in industries that can more efficiently provide these goods.[46]

The notion that individuals tend to *underestimate* the risk of injury or death from tornadoes is in some sense validated by the prevalence of government subsidies to encourage the construction of safe-room shelters. If climate change increases the frequency and spatial density of tornadoes, however, our model suggests that homeowners may be increasingly inclined to purchase safe-rooms on their own initiative. This suggests that state or federal programs to encourage safe-rooms via subsidies may become less necessary in the future, although some complement of carefully designed government incentives may be necessary to smooth demand and keep marginal costs as low as possible. In particular, if all safe-rooms must meet a common standard and are equally effective, and a recent nearby tornado drives up safe-room costs by as much as $2000 while the size of the safe-room rebate to homeowners is capped at $2000, the rebate program begins to look like a "pass-through" to contractors that would be unnecessary if that recent tornado had not driven up costs by this amount.

[46] An article by AP Science Writer Seth Borenstein was carried by many U.S. newspapers on December 8, 2011, most commonly under the title "US shatters record for billion-dollar weather disasters." The May 26, 2011 edition of the New York Times included an article by Kim Severson entitled "Storms Create a Scramble to Install Shelters" that notes "…record-breaking sales for companies that sell safe rooms and shelters designed to withstand the powerful storms that have killed hundreds of people this spring" (http://www.nytimes.com/2011/05/26/us/26shelter.html)

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9. Figures and Tables

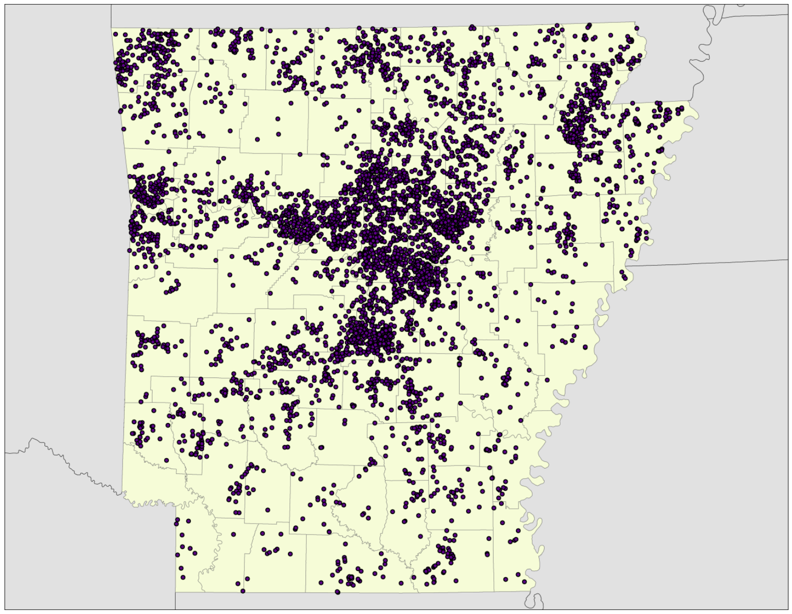

Figure 1. – 6,687 locations of safe-rooms for which subsidies were granted (May 2006 - December 2010)

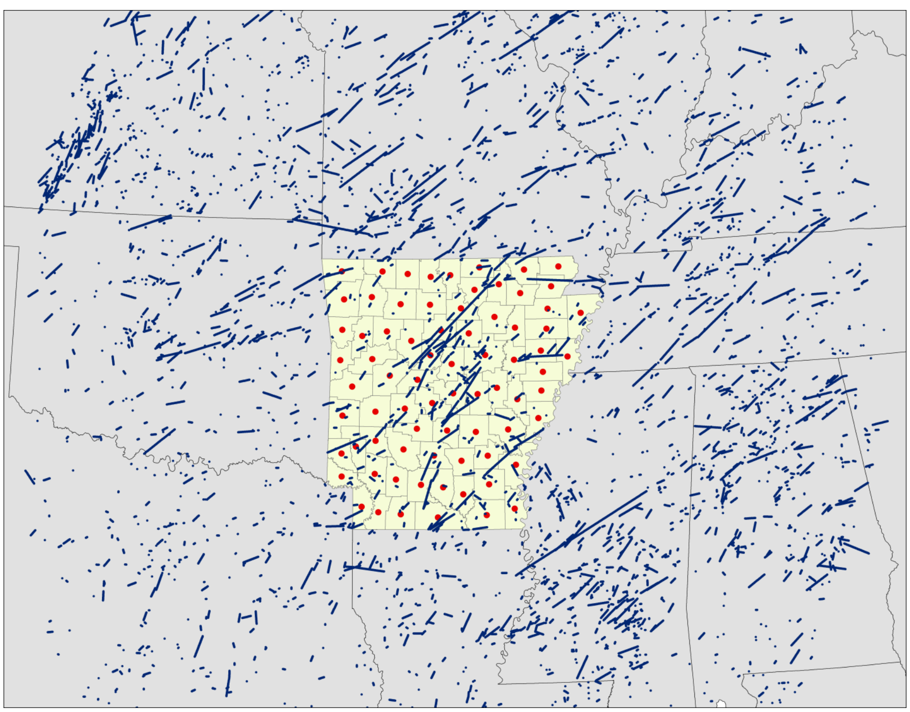

Figure 2. – Locations of tornadoes within 350 miles of any Arkansas county centroids beginning in 2005 through the end of 2010. We construct county-level measures of tornado activity by week and three distance bands (0-50, 50-150, and 100-150 miles from county centroids) for our empirical analysis based on the paths of 1,462 tornadoes within 150 miles of the state.

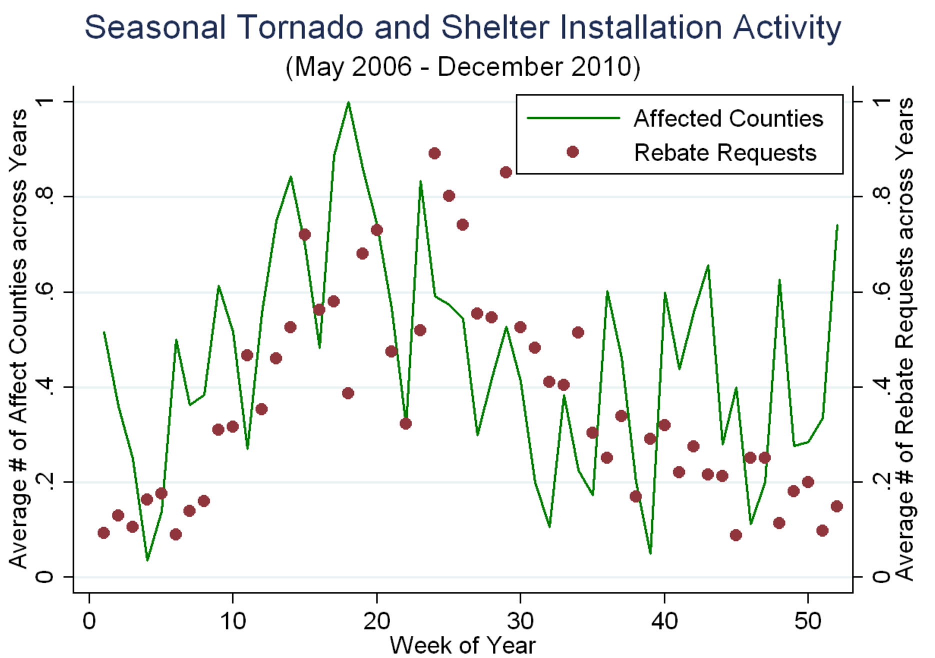

Figure 3. – This figure shows the relative seasonal patterns of the average number of safe-room rebate requests per county and the average number of counties affected by tornado activity. The week-of-year averages are computed across years from May 2006 to the last week of December 2010.

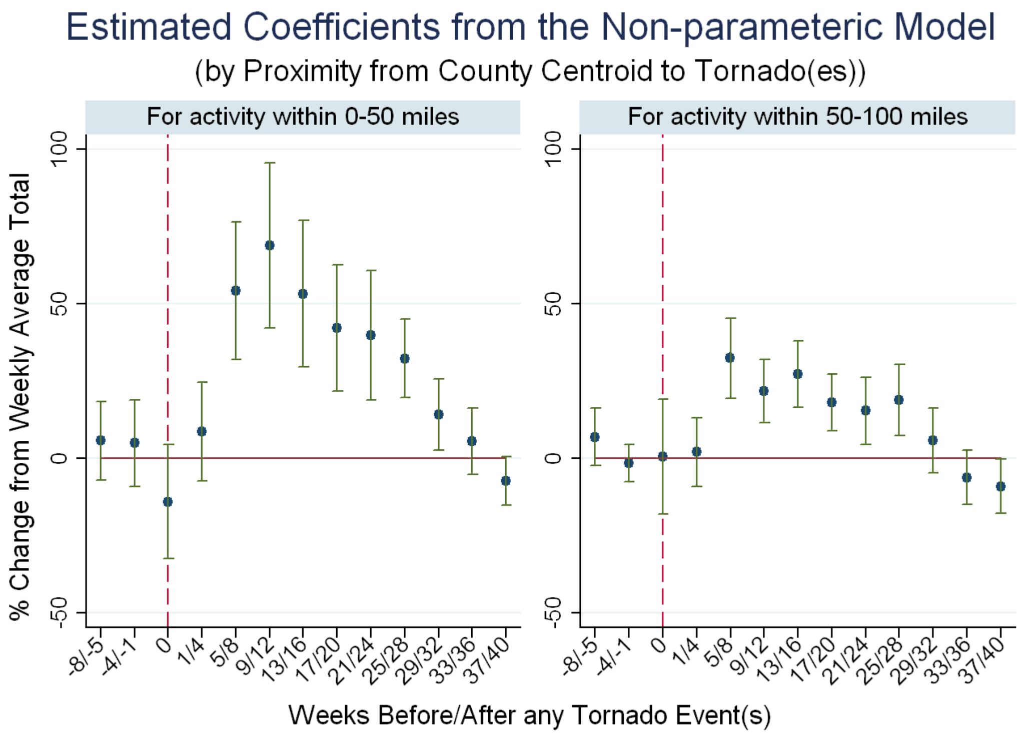

Figure 4. – The left and right panels plot the mean estimates (along with 95% confidence intervals) of the percent change in safe-room rebate requests from the weekly average total for the occurrence of a nearby tornado. These estimates are obtained from using a non-parametric specification for the temporal response. The left panel shows the estimates for the temporal response of rebate requests for any tornado activity within 0 to 50 miles of county centroids. All estimates, except for the contemporaneous "0" week estimate, represent any occurrence of activity aggregated to a month. The right panel shows the same estimated coefficients in a separately estimated model for tornado activity within 50 to 100 miles of county centroids.

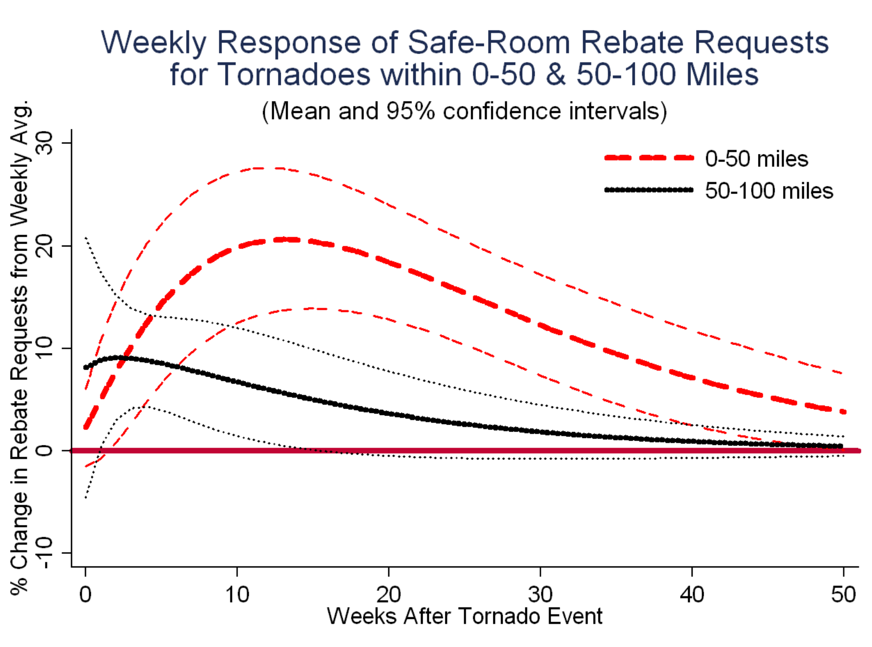

Figure 5. – These graphs show fitted lag coefficients under parametric models for the temporal response function for tornado activity at different spatial proximities. The left panel contrasts the response for rebate requests within a county when a tornado occurs within 50 miles of the county's centroid versus tornado activity that occurs within 50 to 100 miles for a county. The right panel shows the proximity contrast when the spatial proximity of tornado activity is redefined to be either in the same county or in an adjacent county.

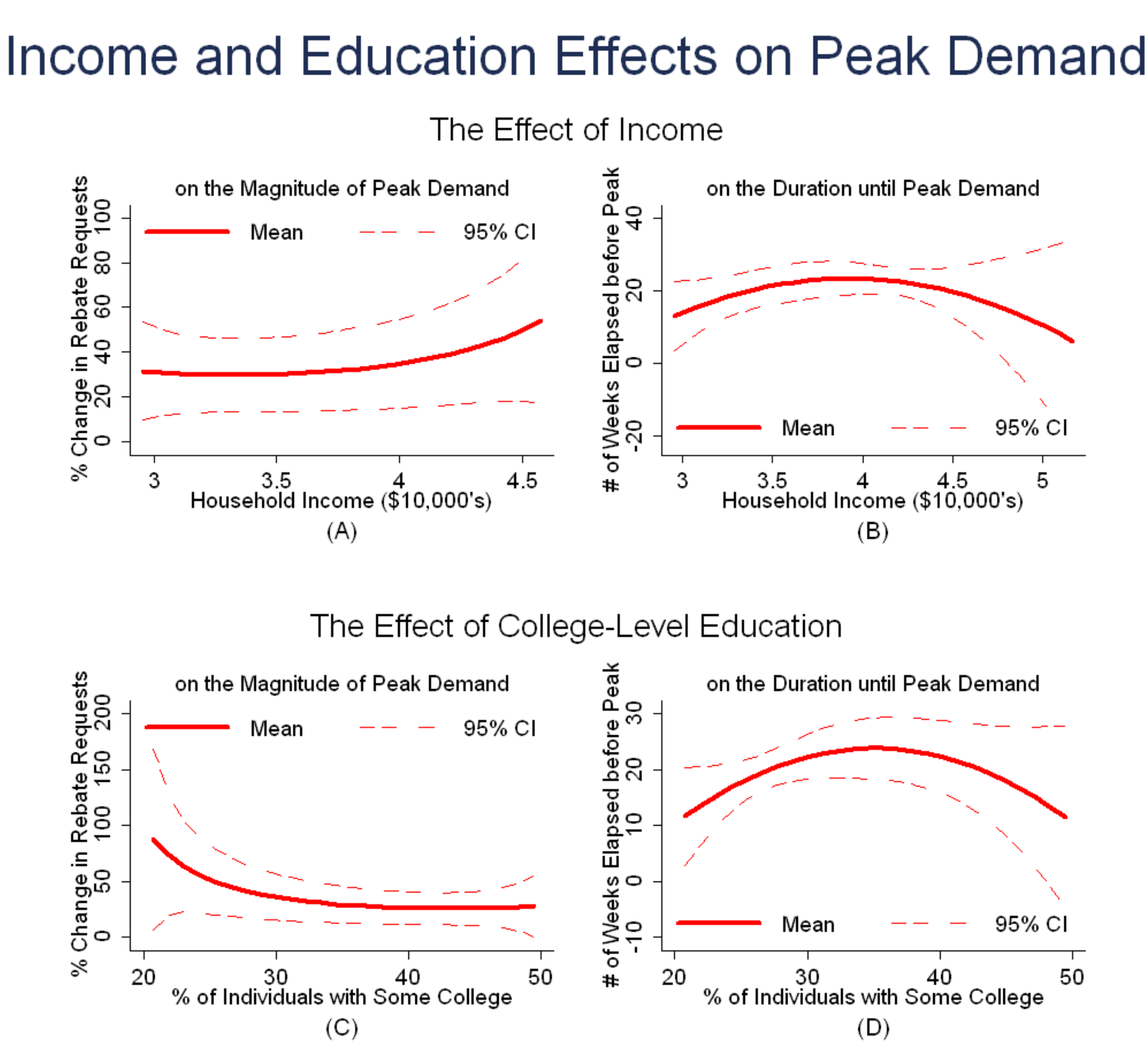

Figure 6. – In panels A and B, we hold constant the education variable ("any college experience") at its sample mean across counties, which is 32.0 percent. We then calculate predicted peak safe-room rebate requests (panel A) and the predicted timing of peak applications (panel B) as a function of median household income for the range of household incomes observed across counties in our sample (from $29,656 through $51,669). In panels C and D, we hold median household income at its average value across counties ($38,670) and calculate predicted peak safe-room rebate requests (panel C) and the predicted timing of peak applications (panel D) as a function of the percent of "any college experience" for the range observed in our sample (from about 20.7 percent to 55.1 percent).

Table 1 – Non-Parametric Temporal Specifications for Tornado Activity within 50 mi. of County Centroids (during specified time intervals); Selected Coefficients

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

Leads or lags of tornado activity:	Model 1 FE Linear	Model 2 Poisson	Model 3 Neg. Bin.
$T^{50}_{c,8/5}$	0.0570	0.0145	0.00301
	(0.839)	(0.221)	(0.051)
$T^{50}_{c,4/1}$	0.0495	0.0455	0.0395
	(0.732)	(0.704)	(0.679)
$T^{50}_{c,0}$	-0.140	-0.150*	-0.143
	(-1.221)	(-1.798)	(-1.593)
$T^{50}_{c,-1/-4}$	0.0869	0.0662	0.121*
	(1.297)	(0.952)	(1.832)
$T^{50}_{c,-5/-8}$	0.542***	0.409***	0.382***
	(8.225)	(6.769)	(5.790)
$T^{50}_{c,-9/-12}$	0.689***	0.483***	0.509***
	(10.845)	(6.245)	(7.070)
$T^{50}_{c,-13/-16}$	0.533***	0.371***	0.341***
	(8.541)	(6.190)	(5.761)
$T^{50}_{c,-17/-20}$	0.422***	0.313***	0.283***
	(6.763)	(5.622)	(4.835)
$T^{50}_{c,-21/-24}$	0.398***	0.326***	0.306***
	(6.492)	(5.925)	(5.253)
$T^{50}_{c,-25/-28}$	0.323***	0.260***	0.359***
	(5.488)	(5.150)	(6.403)
$T^{50}_{c,-29/-32}$	0.141**	0.158***	0.197***
	(2.428)	(2.707)	(3.198)
$T^{50}_{c,-33/-36}$	0.0552	0.100**	0.118**
	(0.950)	(2.034)	(2.075)
$T^{50}_{c,-37/-40}$	-0.0720	-0.0645*	0.00642
	(-1.217)	(-1.659)	(0.152)
Month indicators (seasonality)	Yes	Yes	Yes
County fixed effects	Conditional	Uncond.	Uncond.
Dispersion parameter	-	-	0.341**
# of observations	18,000	18,000	18,000
Log likelihood	-43,271	-12,325	-11,201
# of counties	75	75	75

Notes: Coefficients give the average decimal percentage change in weekly county safe-room rebate requests for a unit change in the independent variable. Estimates in Model 1 were obtained by scaling the dependent variable by .3687, the mean number of weekly requests over the entire sample. T-test statistics for Models 1 and 3; z-statistics with standard errors clustered by county for Models 2 and 3. *** p<0.01, ** p<0.05, * p<0.1. Dispersion parameter indicates significant overdispersion after conditioning on the covariates. The "conditional" county fixed effects in Model 1 use demeaned variables to control for unobserved county differences in the average of number of shelter rebate requests. "Unconditional" fixed effects include county-level binary indicators to control for the unobserved differences across counties.

Table 2 – Parametric Pattern in Lag Coefficients for Tornado Activity by Proximity

Dependent variable: Total Safe-room installations in a county-week

ESTIMATED PARAMETERS	Model 1	Model 2		Model 3		
Distance band:	0-50 miles	_0-50_	50-100	_0-50_	_50-100_	100-150
$\hat{\beta}$	9.379***	7.427***	2.696***	6.897***	1.917***	0.971***
	(9.370)	(6.206)	(3.386)	(5.701)	(2.680)	(2.965)
$\hat{\lambda}$	2.119***	2.395***	1.377**	2.282***	1.245**	90.99
	(6.530)	(5.207)	(2.317)	(5.369)	(2.347)	(1.362)
$\hat{\phi}$	10.67***	10.37***	12.73**	11.05***	12.91**	0.464
	(4.617)	(3.746)	(1.998)	(3.455)	(2.264)	(1.441)
Constant	-2.685***	-2.832***		-2.836***		
	(-25.676)	(-26.334)		(-26.576)		
County FE	Yes	Yes		Yes		
Month-of-year FE	Yes	Yes		Yes		
Overdispersion	0.336**	0.320**		0.312**		
# of observations	18,000	18,000		18,000		
Log likelihood	-11,196	-11,177		-11,166		

Notes: z-statistics with standard errors clustered by county are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. A significant positive value for the overdispersion parameter indicates that the error dispersion is significantly greater than the expected value of the dependent variable after conditioning on the independent covariates.

Table 3 – Demographic Effects on the Parameters of the Parametric Temporal Response

Dependent variable: Total Safe-room installations in a county-week

ESTIMATED PARAMETERS	Model 1 0-50 miles		
	$\hat{\beta}$	$\hat{\lambda}$	$\hat{\phi}$
Baseline coefficient	12.30***	-0.857	17.79**
	(3.598)	(-0.772)	(2.077)
Effect of Income ($10K)	-0.0674	1.571***	-7.041**
	(-0.049)	(2.663)	(-2.252)
Effect of % Any college	-6.734	-9.465***	62.70***
	(-0.488)	(-2.609)	(2.995)
Constant (overall)		-2.712***	
		(-25.788)	
Overdispersion		0.326**	
# of observations		18,000	
Log likelihood		-11,185	

Notes: z-statistics with standard errors clustered by county are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1. A significant positive value for the overdispersion parameter indicates a significant level of overdispersion after conditioning on the independent covariates.

Table 4 – Effects of Current and Past Own-county Tornado Events on Proxies for Supply Constraints in the Local Market for Safe-room Contractors

(Different, later sample; *t* = week)	Model 1 Distance to contractor used[a]	Model 2 Self-installed safe-room[b]	Model 3 Used "obscure" contractor[b]
Count of Tornadoes in County at t-1	-6.892	-0.002	0.119**
	(-0.98)	(-0.08)	(2.12)
Count of Tornadoes in County at t-8	8.750**	-0.001	0.037
	(2.05)	(-0.04)	(1.06)
Count of Tornadoes in County at t-11	-11.875	0.063**	-0.076
	(-1.46)	(2.20)	(-1.21)
Observations	2397	3085	3085
R^2	0.202	0.081	0.135
Week and County FE	Yes	Yes	Yes
Log L	-12362.162	1020.817	-1450.263

Notes: t-statistics in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All models control for the count of same-county tornado events in current week and all lags up to t-15. No other lag coefficients are statistically significantly different from zero. During the time period in question, tornado events per county-week averaged 0.01, with a maximum of two.

[a] Sample is limited by safe-room rebate applications for which a contractor zip-code could be identified. If no contractor address could be found for any of the safe-room rebate applications in a county in a particular week, no average distance could be calculated.

[b] Linear probability model; results are qualitatively identical to probit specification.

Table 5 – Influence of Lags of Four Tornado Metrics on Selected Coefficients (n=2397)

Dependent variable: Distance to contractor used for safe-room installation

Distance to contractor as a function of metric in same county:	Model 1 County Tornado Events	Model 2 County Tornado Injuries	Model 3 County Tornado Fatalities	Model 4 County Property damage
Metric at t-3	4.583	24.150***	-6.366	20.568**
	(0.60)	(3.02)	(-0.19)	(2.08)
Metric at t-8	8.750**	2.885***	32.527***	1.177***
	(2.05)	(3.88)	(3.81)	(4.78)
Metric at t-11	-11.875	-2.509**	-25.192**	-0.486**
	(-1.46)	(-2.25)	(-2.25)	(-1.97)
Metric at t-15	7.587	2.726	-8.001	18.406***
	(0.95)	(0.89)	(-0.25)	(2.71)
R^2	0.202	0.208	0.204	0.212
Week and County FE	Yes	Yes	Yes	Yes
Log L	-12362.162	-12352.716	-12359.019	-12346.103

Notes: t-statistics in parentheses: *** p<0.01, ** p<0.05, * p<0.1. All models control for same-county metric in current week and all lags up to t-15. No other lag coefficients are statistically significantly different from zero. During the time period in question, tornado events per county-week averaged 0.01, with a maximum of two. Tornado injuries averaged 0.00097 with a maximum of 3. Tornado fatalities averaged 0.00032 with a maximum of 1. Tornado property damage averaged $ 3,700 with a maximum of $ 4.75 million (2011 dollars)