Natural Disasters and Real Asset Prices: What Can We Learn From Tornados?

Jeffrey P. Cohen, PhD

Kinnard Scholar in Real Estate and Professor of Finance, University of Connecticut

Research Fellow, Institute for Economic Equity, Federal Reserve Bank of St. Louis

Violeta Gutkowski, PhD[1]

Associate Economist, Federal Reserve Bank of St. Louis

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Abstract: Tornados' impacts on real asset prices have not been extensively explored in a causal analysis framework. We estimate the effects of damage from a major tornado in Little Rock, AR on prices of nearby non-damaged residential real assets. We study how a typical home's proximity to damaged properties might have led to a discount in the price of the subject property due to blight in the neighborhood. We focus on homes that sold between January 2022 and August 2024, and compare the effects of the March 31, 2023 tornado on sale prices for homes *near* versus *far* from damaged houses. For homes within 250 meters from a tornado-damaged home, our difference-in-differences estimates imply an average discount of 29 to 35 percent for all home sales, relative to those homes further away. These effects attenuate with greater distance from the damage points. The presence of additional damaged homes nearby lead to a significant house price discount in the range of 8 percent (within 250m) to 2 percent (within 500m). There is no additional significant discount for homes in lower-income Census block groups, implying homeowners who live in lower income neighborhoods do not perceive different real asset price effects of nearby tornado damage than other homeowners.

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[1] Disclaimer: The views presented in this paper are those of the authors and do not necessarily represent the opinions of the Federal Reserve Bank of St. Louis, the Federal Reserve Board, or the Federal Reserve System.

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1. Introduction

This paper analyzes the house price effects of the March 31, 2023 tornado that impacted Little Rock, AR. Single family homes are one class of real assets that can be impacted by natural disasters, and tornadoes are one type of natural disasters that are prevalent in the central region of the U.S. The focus of this paper is on how tornado damaged homes are related to the prices of homes that were nearby but not damaged. We also consider differences in the effects across neighborhoods with different demographic groups. Little published research to-date has focused on the effects of a tornado on individual houses' sales prices, and no known research has explored the effects of damaged homes on nearby non-damaged homes. Therefore, this is an important question. Also, information on how the number of damaged homes, in addition to proximity to the nearest damage home, affects sales prices, is crucial for policy makers to understand. If there are subsequent repairs of damaged homes, then fewer damaged homes could impact local and regional house price trends. While this paper does not address the impacts of disaster recovery funds,[2] it takes a first step in understanding whether and how the number of nearby damaged homes affect individual house prices after a tornado.

In contrast to tornados, there is a growing body of research focusing on natural disasters more generally, such as fires, hurricanes and floodings, and how these climate-change related issues impact house prices. This paper builds knowledge about one of the tornado disasters that impacted the Midwest in recent years, and how various neighborhoods in the Little Rock, AR area have recovered differently.

For a particular homeowner who lives near houses that have not been rebuilt months after a major tornado disaster, this general decline in the neighborhood's amenity value can be detrimental for a non-damaged home's value. This is because neighborhood quality can be considered a house characteristic; we know that curb appeal, for instance, is an important determinant of real asset prices (e.g., Johnson et al., 2020). The literature on hedonic house prices (Rosen, 1974) is grounded on the theory that a home's value can be broken up into its individual characteristics (number of bedrooms, bathrooms, square footage, etc.). Living near a tornado-damaged home (or multiple damaged homes) can be expected to lower the quality of a particular home because of the amenity or neighborhood effects of these damages.

[2] See Gallagher et al. (2023) for an analysis of disaster recovery funding. While that study considers how disaster funding impacts credit markets and migration, the analysis of how a tornado and the number of damage points impacts individual house prices is novel.

Specifically, we are interested several questions. First, how have residential real asset values across various neighborhoods changed after the tornado? Second, have these values been impacted differently depending on the neighborhood income level? Third, do building permits for repairs to nearby damaged homes affect home values?

Given our focus on amenity values, a hedonic house price approach is suitable here to estimate the effects of proximity to damaged houses on values of homes that were not damaged. We focus on non-damaged homes because often the damaged houses have been completely destroyed, and it is not straightforward to estimate their value after the tornado because they sell for very little and there is not much information on the level of damage the home has suffered. In other cases, some of the damaged or destroyed houses are purchased by investors who repair them and resell shortly thereafter – a process known as "flipping" – and therefore their sale prices do not necessarily reflect the damage of the tornado. This approach of focusing the analysis on non-damaged homes is consistent with at least one paper in the hurricane literature that focuses on sale prices of non-flooded homes (e.g., Cohen, Barr and Kim, 2021).

We find that proximity to tornado damaged homes significantly reduces home prices. Particularly, sales prices fall by 29 to 35 percent for homes which have a damaged home within 250 meters. Sales prices also decrease by about 16 percent for homes with a damaged home within 500 meters. Additionally, the number of damaged homes close to a particular house also significantly lowers that house's sale price. Specifically, we find that an additional damaged home is associated with an 8 percent price discount for houses with an additional damage point within 250 meters, and a 2 percent price discount within 500 meters of a marginal damage point.

Secondly, we do not find supportive evidence that houses near damaged homes in low-income neighborhoods are additionally discounted. Last, but not least, we find that building permits of nearby damaged homes do not affect home values. In particular, we find no supportive evidence that a higher share of building permits of damaged homes increases home values. This finding could be due to several reasons. First, buyers and sellers of houses near many damaged houses with building permits do not place significant value on this information about construction in progress. Perhaps also there is a time lag between when the permit information becomes publicly available and the dates of the initiation of the permit process, or some buyers and sellers may not be aware that there are permits in place for nearby damaged houses. Finally, there may be some assumptions by local residents that most houses will eventually be repaired and therefore the effects of permits only impact the timing of the repairs rather than the expectations of whether repairs will ever take place.

The remainder of this paper proceeds as follows. First, we survey the literature on tornadoes and residential real asset price impacts. Second, we describe our data sources and present some simple descriptive statistics. Third, we describe the methods used in our analysis. Fourth, we present and discuss our empirical results. Finally, we conclude with a summary of the paper and suggest some future areas of research.

1.2 Literature Review

With a few exceptions, there has not been much specifically written on how past tornadoes impact house prices, and how different demographic groups are affected differently. One of the prior studies is Gatzlaff et al (2018). They study Miami-Dade County tornado shelters, and how houses with shelters experience a differential impact on their prices. The authors find a positive correlation, which is due to the visible mitigation amenity that a shelter provides to prospective home buyers.

Contat et al. (2024) summarize some of the existing literature on tornado impacts. These include Ewing et al. (2007), who find the local house price discount associated with a tornado in an MSA can be up to 2 percent of the entire housing stock value on average, although this effect tends to dissipate over time. They also find essentially no difference in the tornado effects and the correspondence between hurricanes and housing values. But their approach constitutes correlation rather than causality. Similarly, Donadelli et al. (2020) exploit MSA level data to determine that tornados are significantly negatively correlated with house prices in the U.S.

Cho et al. (2022) study “path dependence” of tornados in Oklahoma, focusing on 4 tornados over a 15 year period, with a difference-in-differences regression approach. They find that houses close to a prior tornado’s path tend to sell for approximately 2 to 5 percent less in the year following the tornado, but this effect subsequently disappears. Their focus on the tornado path is in contrast to our analysis that is based on proximity to damaged real assets that can be expected to impact the amenity value of a home. Also, although the Cho et al. (2021) analysis relies on a difference-in-differences approach, they do not present any evidence of parallel pre-trends, which brings into question the validity of the causality of their findings.

Sutter and Poitras (2010) studied the tornado risk associated with U.S. manufactured homes. They find that each death per million resident lowers housing demand by 3%. Yi and Choi (2020) allude to the tornados in Iowa that occurred simultaneously as flooding from a severe storm in 2008, but their primary focus is on the flood’s effects and do not directly consider the effects of the associated tornadoes.

Roth Tran and Wilson (2023) explore how natural disasters – including tornados – impact personal income after the disasters. They find there is actually an increase in per-capita income for areas where there is a tornado, likely because tornados create complete destruction over an area that often requires to be rebuilt, which increases economic activity in the medium or long term. They note that tornados typically do not hit the exact same location more than once, so people are more likely to rebuild after a tornado than they would be after a flood that destroys a property.

Finally, Gallagher, Hartley and Rohlin (2023) study 34 tornados from 2002-2013, using Census block data.[3] Their treatment group of Census blocks are those within 0.5 miles from the tornado's path, while the control group is those blocks between 0.5 and 1.5 miles. They use a difference-in-differences model to explore credit and migration outcomes from the tornados. They also allow for treatments that represent the intensity of the tornado damages, based on EF being low, medium, or high. Their primary objective is to estimate the causal effects of federal disaster relief assistance. They find noticeably lower credit card debt in Census blocks that were hit by a tornado and received aid, opposed to other blocks. While they find some evidence of disaster assistance causing lower block-level consumer debt, and greater migration in those blocks, there is no significant evidence of disaster aid on delinquency rates or the blocks' "Equifax Risk Score".

There has been much more work focusing on real estate and other natural disasters, such as hurricanes. Cohen, Barr and Kim (2021) study Hurricane Sandy and New York City house prices. They find that owners of non-damaged houses experience a price discount when the storm surge ends up being closer to their house than expected. The measure of flood expectation is estimated with the difference between the actual storm surge and the anticipated location of flooding based on FEMA flood zone maps.

There are clearly differences between the effects of flooding associated with a hurricane – which could repeat the next time there is a major hurricane - and the one-time effects of a more random tornado. But the Cohen et al. (2021) study motivates the current approach of considering the non-damaged homes proximity to damage points in Little Rock, AR.

[3] Zhao and Grinstein-Weiss (2021) also explore the effects on credit markets (specifically, on the demand for credit), but they focus on "near miss" disaster events.

2. Data

This paper relies on several different sources of data: Home sales data from Pulaski County, AR assessor, tornado damaged homes from National Weather Services, building permits data from the different local and neighborhood demographics from the U.S Census Bureau.

Home sales data

Data from the Pulaski County, AR assessor are obtained for the analysis. The data include fields for sales price, number of bathrooms, square footage of living area, land area, several different flooring type variables, and some other house characteristics. We geocode the data to obtain the latitude and longitude of each property address. We trim the data, dropping the one percent extremes of houses, implying those with sale price under $100 and over $1.39 million are omitted. With the date of the tornado of March 31, 2023, there are likely many houses that were under agreement before that date but sold in the few weeks following the tornado. Thus, we drop sales from April 2023 to avoid this potential issue.

Tornado damage points

We have also obtained GIS data on the path taken by the tornado, which we used to calculate the distances from each house to the tornado's path, from the National Oceanic and Atmospheric Association (NOAA) National Weather Services.

The NOAA data also has information on the impacted homes as well as their damage (for example: full destruction, % of home damaged or destroyed (such as roof, walls, etc.). This source also has information on the exact location coordinates (latitude and longitude) of all 753 tornado damage points, which include houses, other structures, power lines, and trees, among others.

Approximately 300 homes were directly impacted by the tornado. We use the locations of the house damage points to calculate the distance from each non-damaged house that sold after the tornado to the nearest damage point. The non-damaged home sales are the focus of our empirical analysis. Since typically each house only sells once at a given point in time during the data sample period, we end up with an unbalanced dataset of individual single-family house sales covering the timeframe from March 2022 (one year before the tornado) until August 2024.

Table 1: Descriptive Statistics for Home Sales

	Mean		Median		Obs	
	Pre	Post	Pre	Post	Pre	Post
Acres	0.604	0.461	0.230	0.220	1,894	2,156
Price	377,628	290,004	175,000	175,000	1,945	2,200
Age	41.41	44.86	44.50	48	1,494	1,627
Sqft	1,815	1,797	1,564	1,547	1,516	1,684

Building Permits Data

We gathered permits data from the building departments in three of the towns that were on the tornado's path: Little Rock, North Little Rock, and Sherwood. The Little Rock and Sherwood data delineates the addresses, date of permit, and type of damage. The data provided to us by the Sherwood building department was for storm damage permits only. The dataset contains different types of permits, we filtered out any non-building permit. For Little Rock, we filtered out non-storm damage permits and all non-building related permits, for similar reasons as described above. Finally, the North Little Rock data indicated the value of work to be done in the permit, and the permit fee. In personal communications with the North Little Rock building department, we learned that storm damages are typically able to be flagged by permits that have a zero fee and damage totals above $350. We used this algorithm to filter out the non-storm damage permits. From the building permits data, we were able to match 68% of the damaged points from NOAA.

Neighborhood Demographics

In terms of neighborhood demographics, we have median household income at the Census block level, from the American Community Survey of the U.S. Census Bureau.

2.2 Descriptive Statistics

Descriptive Statistics are presented in Table 1 separating the sales sample pre and post tornado. The average sale price for the entire dataset was approximately $331,112, with a mean lot size of one-half acre, two bathrooms, 1,805 square feet of living area and was nearly 43 years old at time of sale. About 4.5 percent of house sales in the sample were within 250 meters of a damage point, 9 percent were within

500 meters, 12 percent within 750 meters and about 16% within 1250m. Approximately 50 percent of house sales were in Low Income Census block groups. Table 3 shows the number of damaged

Table 2: Total Sales Near a Damaged Home

	Total Sales in Sample	Within 250m	Within 500m	Within 750m	Within 1000m
Pre-Tornado	1,945	4.5%	8.6%	11.8%	15.3%
Post-Tornado	2,200	4.6%	9.1%	12.9%	16.6%

homes within different radii showing that conditional on having a damaged home *near ,* homes had on average homes 4 damaged points within 250m, 8 damaged points within 500m, 11 within 750m and 15 damaged homes within the 1000m. Tables A1 and A2 in the Appendix provide this same information disaggregated by neighborhood income level.

3. Methods

We describe in this section our approach to studying how non-damaged houses that are "*near"* damaged houses may experience a price discount when sold. We explore several different distance cutoffs for the "Near" indicator (250 meters, 500 meters, 750 meters and 1000 meters). As a robustness check, we also try controlling for the distance cutoffs with the number of damage points nearby, as well as a number of other variations of the model as described in the results section below.

Our approach for identifying storm damage points relies on, the NOAA National Weather Service geocoded list of storm damage points that it has identified. We reverse geocode these to obtain addresses, and then merge these addresses with the Pulaski County, AR dataset on house sales to be able to determine which sales were damaged and the proximity of non-damaged homes to the nearest damage point. To study the effect of rebuilding homes we rely primarily on the NOAA damage data points and use the building permits data to determine the share of homes under reconstruction. While a comprehensive set of permits data could be desirable, our use of the local building permits was limited because in some cases it was not straightforward to determine which of these were for storm-related damage and when the permits information became publicly available. Because of these potential limitations of the permits data, we focus the main analysis on the NOAA damage data points to compile a comprehensive dataset on the houses that were damaged by the tornado and use the permits to assess the share of homes that were likely to be under reconstruction.

Table 3: Damaged Points Near Homes Sold

	Average number of total damage points	Median number of total damage points
Within 250m	3.9	2
Within 500m	7.8	5
Within 750m	11.4	8
Within 1000m	14.5	9

Our regression approach enables us to generate causal estimates, by relying on a difference-in-differences analysis. The baseline regression estimation equation is as follows:

$$\text{Log(Price)} = b_0 + Xb_1 + b_2\text{Post} + f_i + t_t + e_{it} \qquad (1)$$

In the above model, Price is the sale price recorded at the Pulaski County assessor's office at the time of sale (between March 2022 and August). Post is an indicator variable for sales that occurred after April 30, 2023 (one month following the date of the tornado) and through August 2024; t_t are monthly fixed effects, f_i are block group fixed effects, and e_{it} is a random error term. X is a matrix of covariates associated with each house, including number of bathrooms, square feet of living area, acres of land, and age of the home.

Next, we build up the baseline model by adding a proximity to nearest damage point indicator:

$$\text{Log(Price)} = b_0 + Xb_1 + b_2\text{Post} + b_3\text{Near} + b_4\,\text{Post}\times\text{Near} + f_i + t_t + e_{it} \quad (2)$$

Equation (2) is our difference-in-differences model. Near is an indicator for whether the house is within a specified distance from the nearest damage point; we vary these distances for 250 meters, 500 meters, 750 meters, and 1000 meters. The coefficient b_4 is the treatment effect of being close to a damage point, after the tornado. This specification in (2) is essentially a pooled cross-section in that each observation is either pre- or post-tornado, and either near or far from the tornado. In other words, this is not a balanced panel dataset. Much prior research in the housing literature have used similar models, including Feng et al. (2024), Cohen et al. (2023), Cohen et al. (2021), and others.

Given that being *near* a damaged home may be relevant, but having multiple nearby damaged homes could be further detrimental, we include the number of damaged homes in the distance intervals:

$$\text{Log(Price)} = b_0 + Xb_1 + b_2\text{Post} + b_3\text{Near+} + b_4\,\text{Total\_damaged\_points\_Near} + b_5\text{Post}\times\textit{Total\_damaged\_points\_Near}\; f_i + t_t + e_{it} \quad (3)$$

The variable *Total_damaged_points_Near* captures the number of damaged homes within the 250m, 500m, and so on.

To address the question of differentiated impact across income groups, in equation (4) below we add a third indicator, to represent houses that are in neighborhoods with low median income.

$$\text{Log(Price)} = b_0 + Xb_1 + b_2\text{Post} + b_3\text{Near+}\, b_4\text{LowI} + b_5\,\text{Post}\times\text{Near} + b_6\,\text{LowI}\times\text{Post} + b_7\,\text{LowI}\times\text{Near} + b_8\,\text{LowI x Post}\times\text{Near} + f_i + t_t + e_{it} \quad (4\ )$$

Equation (4) is our difference-in-difference-in-differences model. LowI is a dummy variable that takes the value of 1 if the home was within a Census block group with median income below the median income in Little Rock, and 0 otherwise.

We include a regressor with coefficient b_8 as the "treatment effect", the parameter of interest. This treatment effect shows the impact on house prices of being in a low-income neighborhood near a damage point, after the tornado. In a similar manner as we did before, we also include the number of damaged points as a control variable.

To understand the impact of building permits to repair tornado damaged homes on home values we only look at post tornado sales. For each home sold, we create a variable that captures the share of damaged homes that will be repaired shortly within 250m, 500m and so on. Specifically, we define:

Share_permits_Near= Building permits Near / Total damaged homes Near,

where Near can be within 250m, 500m, 750m or 1000m. Share_permits_Near is a variable between 0 and 1 that captures how many of the nearby damaged homes are expected to be repaired in the short term. We assume the issuance of a permit implies home buyers and sellers of other homes are aware of these impending repairs in the neighborhood.

Equation (5) shows the analysis post tornado:

$$\text{Log(Price)} = b_0 + Xb_1 + b_3\text{Total\_damaged points\_Near+}\, b_4\,\text{Share\_permits\_Near} + f_i + t_t + e_{it} \quad (5)$$

where Share_permits_Near is our variable of main interest, Total_damaged points_Near has been defined earlier, X is a set of control variables. We continue to have block group as well as month fixed effects.

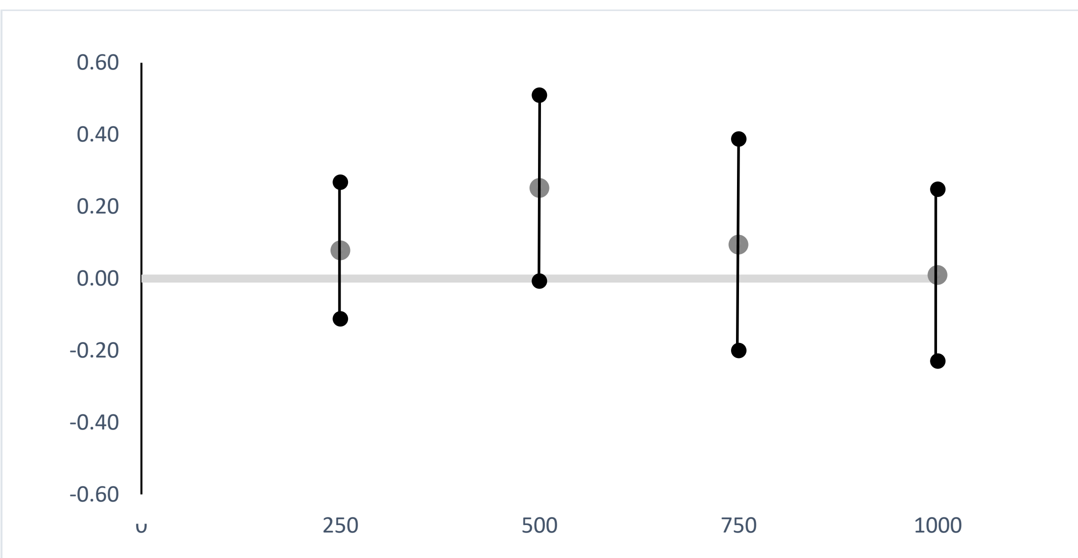
Last but not least, we also we introduce and additional dummy variable “post_permit” which takes the value of 1 if the home was sold after the nearest home issued a building permit, and 0 otherwise. This would capture how important it is that your nearest home is expected to be repaired in the short term.

4.Results

In this section, we show that proximity to a damage point and the total number of damaged homes nearby are important in determining house price discount, and the discount gradually fades away with less proximity. Before diving into the main results, we first show that homes close to the tornado path were not worth different than outside the tornado path.

Figure 1 plots pre-tornado home price differences between homes within 250m, 500m , 750m and 1000m from a home in tornado path relative to those outside those radii. To be more precise, we refer to a home being within 250m from the tornado path if the house sold is within 250m away from a tornado damaged point. After controlling for main house characteristics and time and block fixed effects we find no statistical difference in home prices within different tornado path radii or outside of them.

Figure 1: Pre-tornado house prices *near* a damaged point



Note: 95% confidence intervals. Results show no significant differences in house prices prior to the tornado in neighborhoods nearby post tornado damaged areas. Results after controlling for Age, Square feet, Acres, and Bathrooms, using time and block group fixed effects.

Next, following Eq 1 we evaluate if house prices after the tornado were different than before the tornado and find that they were not, either for the entire sample or for low-income neighborhoods. (Table A3 in the Appendix). Also, we find that the main house characteristics that we are controlling for are significant and have the expected signs. Acres, square feet and bathrooms are all positive and significant showing that larger homes are more costly on average. Age has a negative and significant coefficient showing that older homes usually have lower prices.

Now, we consider home value effects of proximity to damage points following Eq 2. The first set of results, shown in Table 4, considers distance to the nearest damage point as the “NEAR” indicator. We find a 29 percent sales price discount for houses within 250 meters of a damaged home. We also add a control for the number of damage points in this range, which leads to an even stronger contagion effect (i.e., the sale price discount in this case rises to 35 percent). As one might expect, the effects dissipate as the distance range is wider. In other words, houses within 500 m of a damaged home sell for 16 percent less after the tornado, which is statistically significant. Similar to the 250 m results, when controlling for the number of damage points in this radius, the sale price discount becomes larger (i.e., it is 32 percent). For larger distance radii, e.g., houses within 750m of a damaged house, those sold for insignificantly less after the tornado, but when controlling for the number of damage points in this range the estimate becomes statistically significant (and it is 27 percent). These findings are similar for the 1000 m distance band, as the effect is insignificant, but including the number of damaged houses within the 1000 m leads to a statistically significant price discount of approximately 25 percent. Finally, distance bands beyond 1000m are statistically insignificant. These results imply that proximity to a damage point is important in determining the discount, and the discount gradually fades away with less proximity. Houses in neighborhoods with more damage points have larger discounts from proximity to damage points.

Table 4: Tornado Impact on House Prices Main Results

	Price (in logs)							
	Within 250m		Within 500m		Within 750m		Within 1000m	
Near	0.0500	0.166*	0.174**	0.227**	0.144	0.209*	0.0873	0.193
	(0.0776)	(0.0964)	(0.0806)	(0.0974)	(0.0931)	(0.115)	(0.0869)	(0.124)
Post Tornado	-0.0218	0.262	-0.0591	0.295	-0.0657	0.316	-0.0725	0.393*
	(0.297)	(0.202)	(0.278)	(0.205)	(0.274)	(0.208)	(0.272)	(0.229)
Near & Post Tornado	**-0.294*** **	**-0.368*** **	**-0.162***	**-0.316*** **	**-0.101**	**-0.271** **	**-0.0488**	**-0.256** **
	(0.111)	**(0.119)**	**(0.0869)**	**(0.105)**	**(0.0792)**	**(0.108)**	**(0.0767)**	**(0.122)**
Near & # Damage Points		-0.0241		-0.00508		-0.00101		-0.000363
		(0.0171)		(0.00766)		(0.00425)		(0.00406)
Constant	12.04***	12.00***	12.04***	11.61***	12.03***	11.95***	12.03***	11.88***
	(0.218)	(0.315)	(0.218)	(0.222)	(0.218)	(0.317)	(0.219)	(0.331)
Observations	3,075	1,981	3,075	1,981	3,075	1,981	3,075	1,981
R-squared	0.484	0.553	0.484	0.553	0.484	0.553	0.484	0.553

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 . Regressions include house characteristics, block group and monthly dummies.

Next, we explore another specification, where the main coefficient of interest is the marginal house price effect of the number of damage points within 250 m. In this case, in Eq 3 we replace the variable NEAR with the total number of damage points. We find each additional damage point within 250m lowers home sale prices by 8 percent. When we consider a larger radius of 500m, this discount falls to 2 percent per damage point, while the effect is smaller for 750m. At 1000m and beyond, this effect is statistically insignificant. Houses in neighborhoods with more damage points have larger discounts from proximity to damage points. These results are shown in Table 5 below.

Table 5: Marginal Effect of Additional Damage Point

	Price (in logs)			
	Within 250m	Within 500m	Within 750m	Within 1000m
Near	-0.0158	0.0504	0.0408	0.0364
	(0.0847)	(0.0771)	(0.0842)	(0.0863)
# of Damage Points Near	0.0191	0.00344	0.00576	0.00289
	(0.0172)	(0.00871)	(0.00537)	(0.00468)
Post Tornado	0.257	0.240	0.260	0.274
	(0.198)	(0.202)	(0.204)	(0.205)
# of Damage Points Near & Post Tornado	**-0.0754*** **	**-0.0169***	**-0.0111*** **	**-0.00618**
	(0.0238)	**(0.00878)**	**(0.00554)**	**(0.00428)**
Constant	11.59***	11.58***	11.57***	12.00***
	(0.216)	(0.222)	(0.222)	(0.316)
Observations	1,981	1,981	1,981	1,981
R-squared	0.553	0.552	0.552	0.552

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 . Regressions include house characteristics, block and monthly dummies.

To determine whether low-income neighborhoods were additionally impacted by the tornado we also estimate the above-described specification. Eq 4 uses a triple diff-in-diff-in-diff to account for neighborhood income differences. Table 6 shows that the main results described above are robust, while the interactions for demographic variables are not significant. This leads us to believe that the proximity to the nearest damage point, as well as the number of damage points nearby, are the most important factors in determining the house price discount from the tornado.

Table 6: No additional impact on home prices in low income neighborhoods

	Price (in logs)							
	Within 250m		**Within 500m**		**Within 750m**		**Within 1000m**	
Near	-0.0649	0.103	0.132	0.266**	-0.158	-0.0580	-0.0557	-0.00872
	(0.108)	(0.147)	(0.102)	(0.129)	(0.131)	(0.145)	(0.0986)	(0.113)
Post Tornado	0.204	-0.0746	0.207	-0.0450	0.200	-0.0780	0.214	-0.0846
	(0.204)	(0.441)	(0.203)	(0.437)	(0.204)	(0.427)	(0.205)	(0.423)
Near & Post Tornado	-0.242*	-0.279*	-0.165	-0.257**	-0.0764	-0.122	-0.0558	-0.101
	(0.132)	(0.143)	(0.110)	(0.128)	(0.106)	(0.117)	(0.0936)	(0.109)
Near & # Damage Points		-0.0267		-0.00616		-0.00116		-0.000154
		(0.0211)		(0.00817)		(0.00434)		(0.00404)
Low Income	0.348**	-0.688**	0.351**	-0.749**	0.731***	-0.850**	0.757***	-0.960**
	(0.141)	(0.300)	(0.143)	(0.323)	(0.243)	(0.342)	(0.244)	(0.382)
Low Income & Post Tornado	0.0519	0.259**	0.0477	0.335**	0.0405	0.430**	0.0299	0.545**
	(0.0872)	(0.127)	(0.0929)	(0.162)	(0.0964)	(0.200)	(0.0998)	(0.264)
Low Income & Near	0.142	0.116	0.0400	0.00314	0.500***	0.513**	0.225	0.461
	(0.156)	(0.182)	(0.160)	(0.195)	(0.186)	(0.234)	(0.186)	(0.285)
Near & Low Income & Post Tornado	**0.00557**	**-0.152**	**0.0814**	**-0.187**	**0.0642**	**-0.319**	**0.119**	**-0.410**
	(0.235)	**(0.256)**	**(0.181)**	**(0.226)**	**(0.164)**	**(0.240)**	**(0.161)**	**(0.297)**
Constant	12.01***	12.54***	12.02***	12.49***	12.02***	12.49***	12.01***	12.50***
	(0.221)	(0.421)	(0.222)	(0.416)	(0.220)	(0.414)	(0.221)	(0.411)
Observations	2,921	1,876	2,921	1,876	2,921	1,876	2,921	1,876
R-squared	0.488	0.563	0.487	0.563	0.488	0.563	0.488	0.563

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 . Regressions include house characteristics, block group and monthly dummies.

Finally, we explore the share of permits to damaged points issued within 250m, 500m 750m and 1000m at the time the house sold following Eq 5. These results, shown in Table 7 below, are statistically insignificant, and this finding is robust to varying a number of factors. For instance, when we control for the number of damage points, the share of permits issued within 250 m is still insignificant, as is the effect when looking at whether the closest home has a permit that was issued. Our conjecture is that these results reflect the damaged homes near one's home is the most important factor. An important caveat to this finding, which might be driving the relatively large standard errors leading to statistical insignificance, is that there are relatively few observations of permits for damaged houses within 250m or 500m of a particular house sale. Also, the coefficient for this permit share variable may be insignificant if there is some time lag between permit issuance and the permit information becoming publicly available. If this is the case, residents may not be aware of the permits for nearby houses, at the time of a purchase or sale decision.

Table 7: Share of Permits. Post tornado regressions.

	Price (in logs)											
	Within 250m			Within 500m			Within 750m			Within 1000m		
Share of permits Near	**-0.309**	**-0.102**	**-0.281**	**0.206**	**0.262**	**0.329**	**-0.0855**	**0.0739**	**-0.0595**	**0.268**	**0.389**	**0.345**
	(0.505)	**(0.521)**	**(0.498)**	**(0.365)**	**(0.341)**	**(0.354)**	**(0.256)**	**(0.285)**	**(0.243)**	**(0.256)**	**(0.281)**	**(0.248)**
Post Permit		-0.294			-0.0843			-0.239			-0.166	
		(0.488)			(0.240)			(0.218)			(0.152)	
Near & # Damage Points			-0.187**			- 0.0300**			-0.00955			- 0.0148**
			(0.0732)			(0.0141)			(0.00803)			(0.00656)
Constant	12.49***	12.65***	13.45***	12.06***	12.48***	12.29***	12.04***	12.13***	11.88***	11.96***	11.92***	13.16***
	(1.194)	(0.867)	(0.825)	(0.491)	(0.479)	(0.503)	(0.323)	(0.363)	(0.280)	(0.340)	(0.332)	(0.771)
Observations	87	87	87	172	172	172	235	235	235	304	304	304
R-squared	0.759	0.763	0.808	0.571	0.571	0.581	0.536	0.542	0.539	0.531	0.534	0.539

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 . Regressions include house characteristics, block and monthly dummies.

The "recovery" part of the picture, as measured by repair permits issued, are not significant factors. Perhaps this finding arises due to residents' expectations that most of the damages are temporary, based on the region's past experiences with similar tornados of large magnitude. But beyond some tipping point, where the visual damage is severe and noticeable, there are shorter-term effects that may arise due to damages.

4.2 Robustness

We explore several robustness checks in this section. For the first robustness check, we allow the impact of the number of damaged points to be non-linear by adding a quadratic term where Near x (Total damage points) indicates the number of damage points near the considered home and $(\text{Total damage points})^2$ is the squared value of the number of damaged homes. The latter allows for potential non-linearities. Table A4 in the Appendix presents the findings showing that non linearities barely affect coefficients and significance from the main specification.

When considering damaged homes within a 500m radius of a particular home sale, that also included damaged homes within the 250m radius. However, that leads to the question of whether the

500m radius results are being driven by the fact that houses between 0 and 250m are also included in the 500m radius. If one could isolate the effects for damages between 250m and 500m, for example, that could glean some additional insights as to which damage points are most important determinants of the sale prices of nearby houses. As an alternative to the radius approach, we explored distance bands in 250m increments. We consider bands: 0 to 250m, 250m to 500m, etc., which leads to the following specification:

$Log(Price) = b_0 + Xb_1 + b_2Post + b_{3j}Band_j + b_{4j}Post \times Band_j + b_5 Total\_damaged\_points\_in\ Band_j + f_i + t_t + e_{it}$, (Eq 6)

where j represents the band (i.e., 0 to 250m, 250m to 500m ,500m-750m and 750m to 1000m).

The discount in the 0 to 250m band is statistically significant, with the discounts in bands further out being insignificant. Again, this finding may arise because there are few houses in the bands that are further out, which could be inflating the standard errors. But these results, in general, confirm the radius findings that indicate most of the effects are attributable to houses that are very close (i.e., within 250 m) to a damage point

Another robustness check that we consider is limiting the sample to post-tornado sales and explore the marginal effects of additional damage points nearby. In this case, the results are similar to the sample that considers sales pre- and post-tornado, with the largest price discounts being in areas closer to the additional damage point.

We compare pre-tornado sales with post-tornado sales that occurred more than 9 months after the tornado. These results are presented below in Table 8. Based on these regression results, it is apparent that there is essentially no long-term effect of the tornado on residential real asset prices.

Table 8 – Pre-Tornado Sales Versus Sales More Than 9 Months Post-Tornado

	Price (in logs)							
	Within 250m		Within 500m		Within 750m		Within 1000m	
Near	0.300*	0.407*	-0.0170	0.122	0.0631	0.270	-0.00221	0.167
	(0.176)	(0.214)	(0.154)	(0.176)	(0.137)	(0.165)	(0.142)	(0.184)
Post Tornado	0.0541	-0.00313	0.154	0.325	0.140	0.338	0.137	0.432
	(0.358)	(0.345)	(0.404)	(0.383)	(0.393)	(0.374)	(0.393)	(0.381)
Near & Post Tornado	**0.149**	**-0.0145**	**-0.144**	**-0.462**	**-0.0750**	**-0.437***	**-0.0746**	**-0.590****
	(0.170)	**(0.206)**	**(0.263)**	**(0.288)**	**(0.210)**	**(0.251)**	**(0.193)**	**(0.247)**
Near & # Damage Points		-0.00886		-0.00165		-0.00499		-0.000604
		(0.00591)		(0.00426)		(0.00362)		(0.00263)
Constant	8.373***	12.86***	8.402***	12.79***	8.386***	12.77***	8.394***	12.83***
	(1.210)	(0.593)	(1.208)	(0.598)	(1.207)	(0.594)	(1.208)	(0.585)
Observations	1,749	901	1,749	901	1,749	901	1,749	901
R-squared	0.381	0.513	0.380	0.513	0.380	0.514	0.380	0.515

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Regressions include house characteristics, block and monthly dummies.

The next set of results is a robustness check of the findings in Table 4 above. In Table 9 below, we drop the data in 2024, so that we only consider the post-tornado effects of sales from 2023 against the sales prior to the tornado. We find that the estimates are larger (in Table 4) when we include the entire sample, relative to when we drop the 2024 data and focus on the post-tornado sample with 2023 data (in Table 9). This implies that perhaps the dynamics of the real asset price adjustments are complex, and including the entire sample is important in order to avoid problems of attenuation bias in the data.

Table 9 – Pre-Tornado Sales Versus Sales Less Than 9 Months Post-Tornado

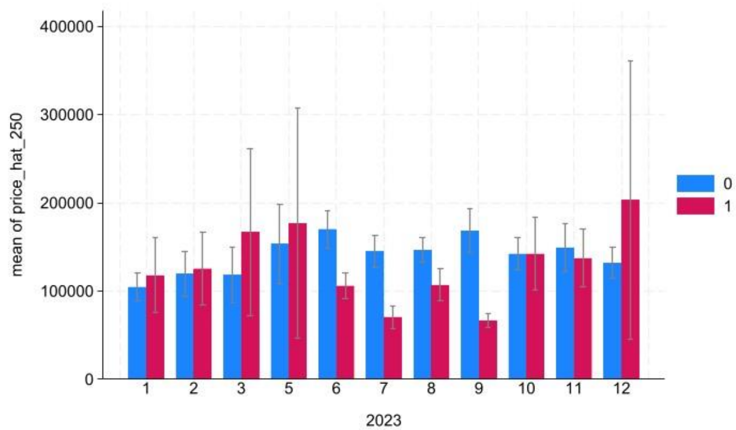
	Price (in logs)							
	Within 250m		Within 500m		Within 750m		Within 1000m	
Near	0.206	0.342*	0.0103	0.0965	0.0705	0.150	0.0633	0.156
	(0.142)	(0.178)	(0.138)	(0.162)	(0.139)	(0.171)	(0.127)	(0.173)
Post Tornado	0.242	0.154	0.236	0.220	0.244	0.252	0.232	0.864*
	(0.228)	(0.193)	(0.229)	(0.199)	(0.231)	(0.207)	(0.231)	(0.505)
Near & Post Tornado	**-0.571****	**-0.618****	**-0.327****	**-0.467****	**-0.286****	**-0.457****	**-0.199**	**-0.374***
	(0.229)	**(0.256)**	**(0.164)**	**(0.198)**	**(0.145)**	**(0.196)**	**(0.134)**	**(0.215)**
Near & # Damage Points		-0.0172*		-0.00180		-0.00123		0.000303
		(0.00979)		(0.00514)		(0.00361)		(0.00270)
Constant	8.725***	11.99***	8.727***	11.92***	8.729***	12.52***	8.867***	11.15***
	(0.436)	(0.479)	(0.437)	(0.472)	(0.435)	(0.431)	(0.447)	(0.622)
Observations	2,272	1,423	2,272	1,423	2,272	1,423	2,272	1,421
R-squared	0.380	0.442	0.380	0.441	0.379	0.440	0.379	0.439

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Regressions include house characteristics, block and monthly dummies.

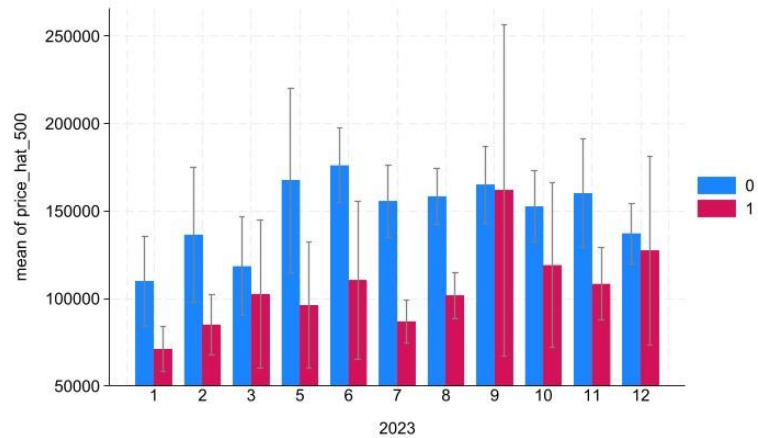
Next, we offer some evidence that our data satisfies the parallel pre-trends requirement that is a condition for causal identification of our model. We plot the predicted residential real asset price trends, month by month, based on the regression estimates of our model in equation 2 (inclusive of the number of damage points as a covariate). These indicate that in the 3 months before April 2023, for each of the distance bands that we explore, the prices for the treatment and control groups are not statistically different from each other. We omitted April from the regressions, but we also observe no significant differences in May 2023 sales prices. The lack of statistically significant differences between May 2023 treatment and control group prices is because it often can take 45 to 60 days after a purchase contract is signed to get the mortgage funds and other paperwork required for the closing process, and therefore the sale date often reflects prices that were determined 45-60 days prior.

We attribute the lack of significance to the fact that many homes sold in May 2023 had their prices determined pre-tornado. By June, there should be none with prices that were determined before the tornado. In fact, we observe in most cases there are significant divergences between the treatment and control groups starting in June 2023.

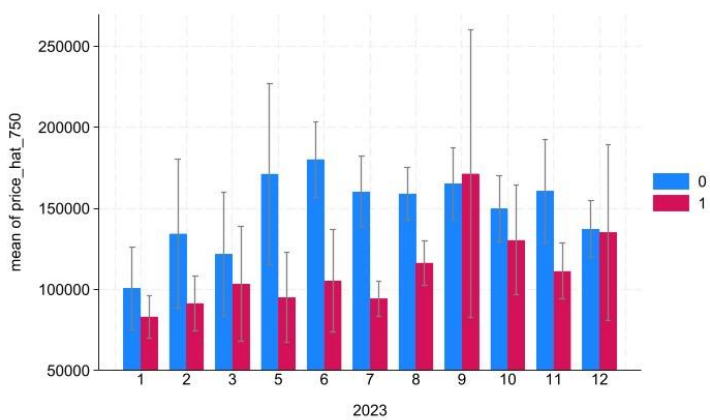
Figure 2 – Parallel Pre-Trends, Various Distance Radii (2023 Months; tornado is 3/31/23; April Omitted; May is within 60 days of tornado)



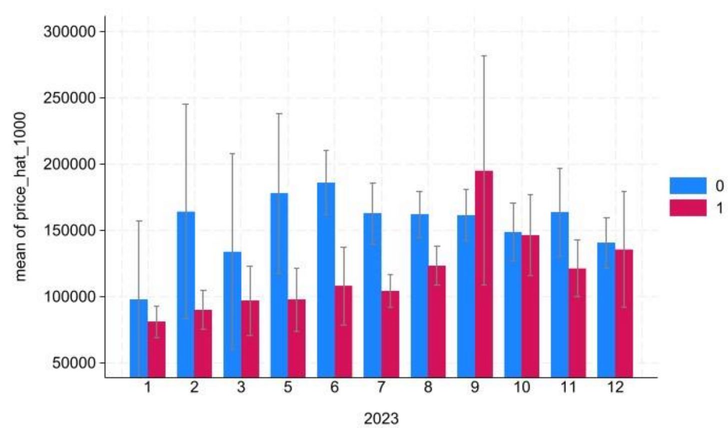
Panel A – Predicted Price for Homes Within 250m of Damage Point



Panel B – Predicted Price for Homes Within 500m of Damage Point



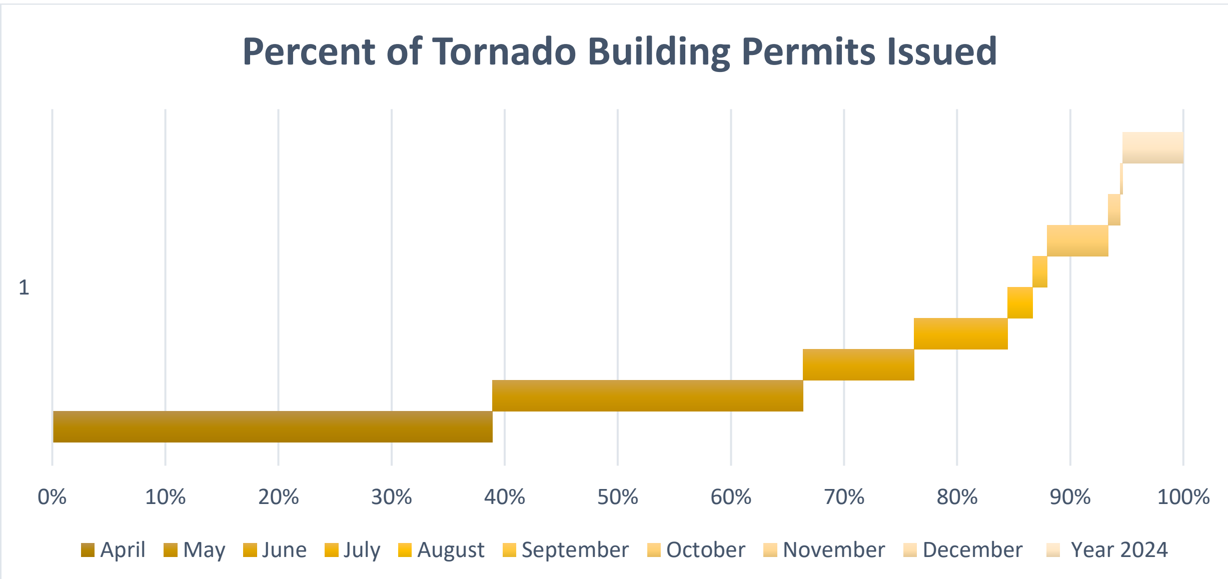
Panel C - Predicted Price for Homes Within 750m of Damage Point



Panel D – Predicted Price for Homes Within 1000m of Damage Point

Finally, we present some figures showing how building permits have changed over time. We first demonstrate the cumulative distribution of permits issued in Figure 3. This shows that 75% of the building permits were issued within the months of April, May, and June, 2023 while 85% were issued before August 2023.

Figure 3 – Cumulative Number of Building Permits Issued Over 2023-24 In All Census Tracts



There are some differences in the cumulative distribution when considering whether the Census tract where the building permits issued are low or high income (based on the median income level of the entire sample). Specifically, for high income tracts, most of the building permits were issued during the month of April, with 85% before August . Fewer permits were issued during the month of April for Low income neighborhoods, however those neighborhoods also had approximately 85% of building permits issued before August. Perhaps this disparity in building permits issued reflects liquidity constraints faced by residents in lower income neighborhoods that are not obstacles for residents of higher income neighborhoods. The cumulative distribution figures for both types of neighborhoods are presented below in Figures 4a and 4b.

Figure 4a - Cumulative Distribution of Permits Issued Over 2023-24 In "High" Income Census Tracts

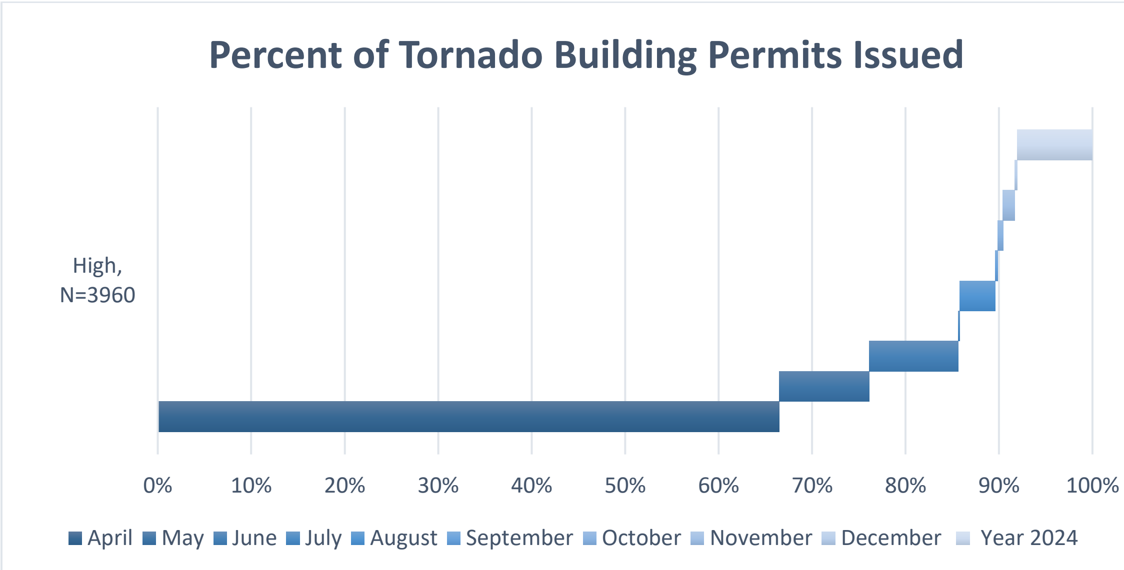
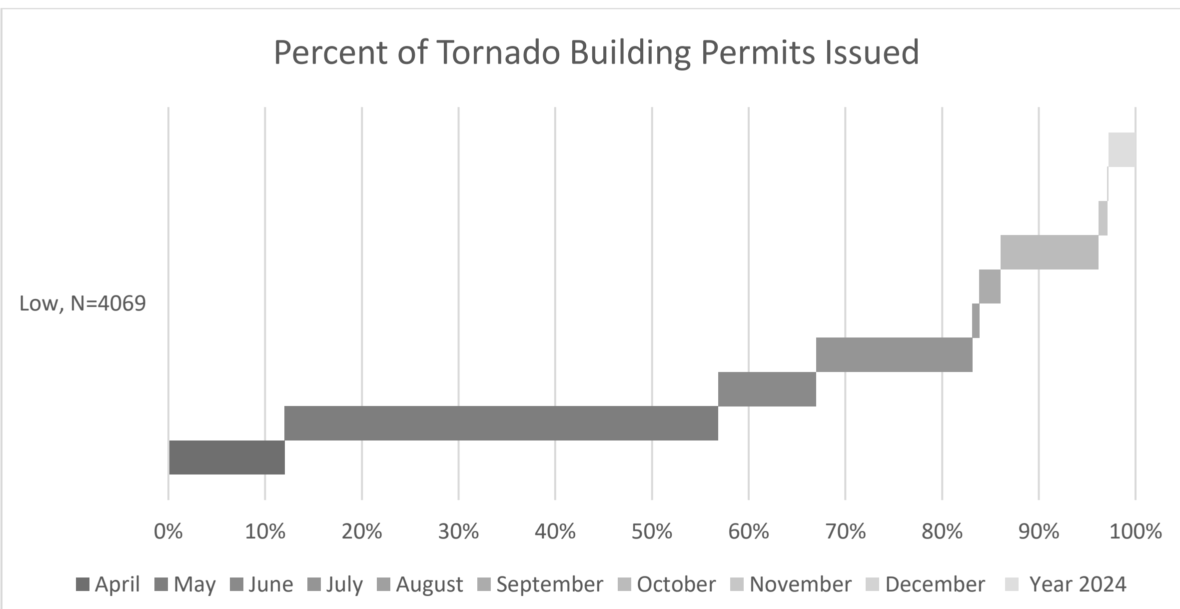


Figure 4b - Cumulative Distribution of Permits Issued Over 2023-24 In "Low" Income Census Tracts



5.Conclusion

Extreme weather events are becoming more common throughout the U.S. Tornados are one group of extreme weather events that can cause tremendous damage in concentrated areas. The effects of tornados on residential real asset prices have been under-studied, relative to other types of extreme weather events.

In this paper, we explore the residential real asset price effects of a specific tornado that hit the Little Rock, AR area on March 31, 2023. We focus our attention on the effects of this tornado on prices of homes that were not damaged, because severely damaged houses often sell at a negligible price and likely do not represent arms-length market-based transactions. Furthermore, such damaged assets often are repaired and subsequently "flipped" and therefore are not always representative of the market's true valuation, but rather they may reflect a speculative aspect of those properties.

Living in a non-damaged home in a neighborhood with damaged properties nearby can lead to capitalization of the overall lower neighborhood quality associated with the aesthetics of the neighborhood. We test the hypothesis that non-damaged homes that were near damaged ones sold for less than other houses. In addition, we test the hypothesis that the number of nearby damage points is a significant determinant of real asset prices. We also test the hypothesis that this relationship could be different for homes in low-income block groups. The causal estimates in this paper are based on difference-in-differences estimation approaches and are robust to a variety of model specifications.

We find evidence of 29 to 35 percent, statistically significantly lower residential real asset prices in neighborhoods within 250m of the nearest tornado damage point, and this effect attenuates as distance from the nearest damage points rises. Additionally, there is a 2 to 8 percent price discount for each additional damage point within 250m of a particular sale. Secondly, we do not find supportive evidence of any differences in this discount for homes near damaged properties in low-income neighborhoods. This could possibly be related to the ample FEMA funds that the city of Little Rock residents received to repair damaged homes.

Last, but not least, we find that building permits of nearby damaged homes do not affect home prices. In particular, we find no supportive evidence that a higher share of building permits of damaged homes increases home prices. This finding may have a number of implications. First, buyers and sellers of houses near many damaged houses with building permits do not place significant value on this information about construction in progress. Perhaps also there is a time lag between when the permit information becomes publicly available and the dates of the initiation of the permit process, or some buyers and sellers may not be aware that there are permits in place for nearby damaged houses. Finally, there may be some assumptions by local residents that most houses will eventually be repaired and therefore the effects of permits only impact the timing of the repairs rather than the expectations of whether repairs will ever take place.

These results have implications for policy related to tornado damage cleanup funding. This paper does not address, nor has it quantified the impact of, city, state and federal funds to help residents directly, yet findings of this paper could have been affected by the vast resources to help the affected population. In particular, one may have expected that low-income neighborhoods could have been additionally affected by the tornado since surrounding damaged homes could potentially not be repaired and end up vacant. Nevertheless, this paper finds that these neighborhoods were not additionally impacted and potentially, this could be the case because of effective city, state and federal funds. This paper contributes to an ongoing literature of further understanding the recovery across different neighborhoods after a natural disaster, as well as the relevant measures to ensure that such recoveries do not leave underserved neighborhoods behind.

Specifically, if real asset prices can be restored to their pre-tornado levels by subsidizing cleanup and repair of damaged houses, this societal benefit could validate directing more state and/or federal funding for the recovery efforts. At the same time, a better understanding about how the number and locations of damage points impacts real asset values can also be important information for policy makers considering how and where to allocate recovery funds, and for investors who purchase real assets. This information, and the associated anticipated effects on housing market recoveries, can be crucial at a time when there is a national housing shortage and an affordability crisis.

The techniques that we apply in this paper are ripe for application to other geographic settings in the U.S. where tornados are common. It would be of interest to discern whether the effects of damage point proximity on real asset prices was larger or smaller than what we found here for Little Rock. This could have further implications for where to direct cleanup funds, since with scare resources, policy makers can benefit from understanding which locations can achieve the greatest “bang for the buck” from cleanup dollars. And an assessment of how real asset prices change differently for various natural disasters can allow for an important comparison of how to direct such aid differently to different disaster types.

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Appendix

Table A.1: Number of damaged homes *near* homes sold by neighborhood income

	Average number of total damage points		**Median number of total damage points**	
	Low Income	High Income	Low Income	High Income
Within 250m	3.2	4.5	1	3
Within 500m	7.4	7.7	5	8
Within 750m	11.0	11.3	6	10
Within 1000m	14.4	14.5	8	10

Table A2: Number of homes sold near damaged points

		Pre-Tornado	**Post-Tornado**
Within 250m	High	33	57
	Low	53	39
Within 500m	High	60	110
	Low	106	86
Within 750m	High	91	153
	Low	134	124
Within 1000m	High	118	199
	Low	170	151
Total home sales		1,945	2,200

Table A3: House prices after the tornado

	Price (in logs)	
Post Tornado	**-0.0829**	0.195
	(0.268)	(0.203)
Low Income		0.353**
		(0.141)
Low Income & Post Tornado		**0.0517**
		(0.0830)
Acres	0.0713***	0.0633**
	(0.0272)	(0.0265)
Sqft	0.000203***	0.000204***
	(4.67e-05)	(4.69e-05)
Age	-0.00975***	-0.00892***
	(0.00152)	(0.00157)
Baths	0.223***	0.225***
	(0.0488)	(0.0488)
Constant	12.03***	12.01***
	(0.218)	(0.221)
Observations	3,075	2,921
R-squared	0.484	0.487

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 .

Regressions include house characteristics, block and monthly dummies.

Table A4: Robustness: Accounting for non-linearities in the impact of number of damaged points

	Price (in logs)			
	Within 250m	Within 500m	Within 750m	Within 1000m
Post Tornado	0.252	0.294	0.311	0.393*
	(0.204)	(0.205)	(0.206)	(0.228)
Near	0.231*	0.241**	0.257**	0.190
	(0.129)	(0.104)	(0.130)	(0.146)
Near & Post Tornado	**-0.354*** **	**-0.315*** **	**-0.273** **	**-0.256** **
	(0.116)	**(0.106)**	**(0.108)**	**(0.122)**
Near & # Damage Points	-0.0649	-0.00867	-0.00997	0.000103
	(0.0515)	(0.0150)	(0.0148)	(0.0119)
# Damage Points Squared	0.00262	9.96e-05	0.000175	-7.38e-06
	(0.00255)	(0.000280)	(0.000237)	(0.000141)
Constant	12.01***	11.62***	11.95***	11.54***
	(0.316)	(0.224)	(0.316)	(0.222)
Observations	1,981	1,981	1,981	1,981
R-squared	0.553	0.553	0.553	0.553

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1 .

Regressions include house characteristics, block and monthly dummies.

Table A5: Tornado impact on house prices by distance bands

	Price(logs)			
	0m - 250m band	**250m- 500m band**	**500m-750m band**	**750m-1000m band**
Post_tornado	-0.0370 (0.285)	-0.0771 (0.275)	-0.0838 (0.269)	-0.0839 (0.269)
Band	0.189 (0.127)	0.163* (0.0844)	-0.0305 (0.106)	-0.0788 (0.157)
Band x Post_tornado	-0.264** (0.105)	-0.00785 (0.113)	0.0731 (0.139)	0.125 (0.174)
# damaged points in 0-250m	-0.0647 (0.0495)			
# damaged points in 250m-500m		0.00458 (0.00896)		
# damaged points 500-750m			-0.00178 (0.00563)	
# damaged points 750-1000m				0.00164 (0.00513)
Constant	12.04*** (0.218)	12.05*** (0.219)	12.03*** (0.218)	12.03*** (0.219)
Observations	3,075	3,075	3,075	3,075
R-squared	0.484	0.484	0.484	0.484

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Regressions include house characteristics, block and monthly dummies.