Natural Disasters and Housing 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, Community Development Group, Federal Reserve Bank of St. Louis

Violeta Gutkowski, PhD[1]

Associate Economist, Federal Reserve Bank of St. Louis

January 31, 2025

Abstract: The impact of tornados on housing prices has not been extensively explored in a causal analysis framework. We estimate the effects of damage from a major tornado in Little Rock, Arkansas on prices of nearby undamaged homes. We study how a typical home's proximity to damaged properties might have led to a discount in its price due to severe 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 homes. For all home sales within 250 meters of at least one tornado-damaged home, our difference-in-differences estimates imply an average discount of 29 to 35 percent relative to home sales further away. These effects attenuate with greater distance from the nearest damaged home. The presence of each additional damaged home nearby led to a significant home price discount in the range of 8 percent (within 250 meters) to 2 percent (within 500 meters). Homes in lower-income Census blocks did not incur price effects that were significantly different from the effects for other homes.

JEL Code: R2

Keywords: housing prices, tornados

---

[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.

The authors acknowledge the excellent research assistance of Cole Kurokawa, Weidong Li, Lindsey Sanderson and Jake Shufro. Participants at the 2024 Federal Reserve System Regional Meetings in Atlanta provided helpful comments.

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 housing that can be impacted by natural disasters, and tornadoes are one type of natural disaster 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 nearby but undamaged homes. 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 undamaged homes. 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. Subsequent repair of damaged homes may 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, Arkansas, area have recovered differently.

A major tornado disaster can cause a general decline in a neighborhood's amenity value that can be detrimental for the value of undamaged homes that are nearby damaged homes that have not been quickly rebuilt. This is because neighborhood quality can be considered a house characteristic; we know that curb appeal, for instance, is an important determinant of housing 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.

Specifically, we are interested in several questions. First, how have residential housing prices across various neighborhoods changed after the tornado? Second, have these values been impacted

[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 damaged homes impacts individual house prices is novel.

differently depending on the neighborhood income level? We think that building permits could be a good proxy for rebuilding efforts in the neighborhood, which could impact home prices. Thus, our third question is: Do building permits for repairs to nearby damaged homes affect home prices?

Given our focus on amenity values, a hedonic house price approach is suitable here to estimate how proximity to damaged homes affects the values of undamaged homes. We focus on *completely undamaged* homes and not *partially damaged* homes because there is little information on the level of damage homes have suffered. Also, damaged homes have often been completely destroyed and it is not straightforward to estimate their value after the tornado because they usually sell for very little.. 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 undamaged 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 have 3 major findings. First, we find that proximity to tornado-damaged homes significantly reduces home prices. Particularly, sales prices fall by 29 to 35 percent for homes that are within 250 meters of a damaged home. Sales prices also decrease by about 16 percent for homes that are within 500 meters of a damaged home. Additionally, proximity to a greater number of damaged homes close to a particular house also significantly lowers that house’s sale price. Specifically, we find an 8 percent price discount when houses are within 250 meters of an additional damaged home, and a 2 percent price discount within 500 meters of an additional damaged home.

Second, we do not find supportive evidence that houses near damaged homes in low-income neighborhoods are additionally discounted. Third, 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 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 housing 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, the literature has not specifically described how tornadoes have impacted house prices and different demographic groups. One of the prior studies is Gatzlaff et al. (2018). They study the effects of tornado shelters on house prices in Miami-Dade County and find a positive correlation 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 prices. 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, which is based on proximity to damaged housing 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. They find there is actually an increase in per-capita income for areas where there has been a tornado, likely because the destruction caused by tornados often require rebuilding, 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 homeowners are more likely to rebuild after a tornado than they after a flood, which is more likely to recur.

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's damage, based on the Enhanced Fujita Scale (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 compared with 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 that disaster aid affects delinquency rates or the blocks' Equifax risk/credit 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 undamaged houses experienced a price discount when the storm surge ended up 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 undamaged homes proximity to damaged homes 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 the Pulaski County, Arkansas, assessor; tornado-damaged homes data from the National Weather Service; building permits data from the different local cities; and neighborhood demographics data from the U.S Census Bureau.

The data from the Pulaski County, Arkansas, assessor, includes sales price, number of bathrooms, square footage of living area, land area, several different flooring type variables, and other house characteristics. We geocode the data to obtain the latitude and longitude of each property address. We trim the data, dropping the 1 percent extremes of houses, omitting those with a sale price under $100 and over $1.39 million. The date of the tornado was March 31, 2023, and 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 damaged homes

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 or percentage of the home that was damaged or destroyed (such as roof, walls, etc.). This source also has information on the exact location coordinates (latitude and longitude) of all damaged homes.

Approximately 300 homes were directly impacted by the tornado. We use the locations of the damaged homes to calculate the distance from each undamaged home that sold after the tornado to the nearest damaged home. The undamaged home sales are the focus of our empirical analysis. Since typically each house sells only once during the data sample period, we end up with a pooled cross-section time series 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 delineate 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, and 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 damage is 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 homes from NOAA.

Neighborhood Demographics

For 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 age of home nearly 43 years at time of sale. About 4.5 percent of house sales in the sample were within 250 meters of a damaged home, 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 2 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; it shows that, conditional on having a damaged home *nearby,* homes had on average homes 4 damaged homes within 250 meters, 8 damaged homes within 500 meters, 11 within 750 meters and 15 damaged homes within the 1000 meters. 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 undamaged 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 damaged homes nearby, as well as a number of other variations of the model as described in the results section below.

Our approach for identifying storm damaged homes relies on the NOAA National Weather Service geocoded list of storm damaged homes that it has identified. We reverse-geocode these points to obtain addresses and then merge these addresses with the Pulaski County, Arkansas, dataset on house sales to be able to determine which sold homes were damaged and the proximity of undamaged homes to the nearest damaged home. 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. A comprehensive set of permits data could be desirable; however, 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 homes Near Homes Sold

	Average number of total damaged homes	**Median number of total damaged homes**
Within 250 meters	3.9	2
Within 500 meters	7.8	5
Within 750 meters	11.4	8
Within 1000 meters	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 damaged home 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 damaged home; 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 damaged home, 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 and having multiple nearby damaged homes could be even more detrimental; so, we include the number of damaged homes in the distance intervals:

$$Log(Price) = b_0 + Xb_1 + b_2Post + b_3Near + + b_4 Total\_damaged\_points\_Near + b_5Post \times \mathit{Total\_damaged\_points\_Near}\ f_i + t_t + e_{it} \quad (3)$$

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.

$$Log(Price) = b_0 + Xb_1 + b_2Post + b_3Near + b_4LowI + b_5 Post \times Near + b_6 LowI \times Post + b_7 LowI \times Near + b_8 LowI \text{ x } Post \times Near + f_i + t_t + e_{it} \quad (4\ )$$

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 damaged home, after the tornado. In a similar manner as we did before, we also include the number of damaged homes as a control variable.

To understand the impact of building permits to repair tornado damaged homes on home prices 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, 500 metersand 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:

$$Log(Price) = b_0 + Xb_1 + b_3Total\_damaged\ homes\_Near + b_4 Share\_permits\_Near + f_i + t_t + e_{it} \quad (5)$$

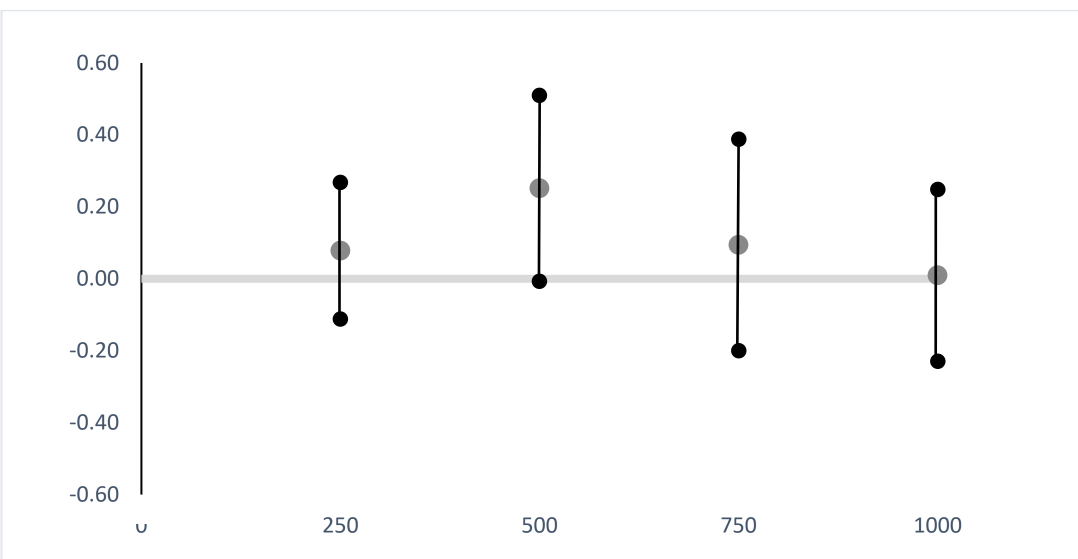
where *Share_permits_Near* is our variable of main interest, *Total_damaged homes_Near* has been defined earlier, *X* is a set of control variables. We continue to have a block group as well as monthly fixed effects. Lastly but not least, we also we introduce an additional dummy variable *post_permit*, which takes the value of 1 if the home was sold after the nearest damaged home issued a building permit and 0 otherwise. This would capture how important it is that the nearest damaged home is expected to be repaired in the short term.

4.Results

In this section, we show that (i) proximity to a damaged home and the total number of damaged homes nearby are important in determining the house price discount and (ii) the discount gradually fades away with less proximity. Before diving into the main results, we first show that there was no difference between values for homes *close* to the tornado path and values for those *outside* the tornado path.

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

Figure 1: Pre-tornado House Prices N*ear* a Damaged Home



Note: 95% confidence intervals. Results show no significant differences in house prices prior to the tornado in neighborhoods nearby the 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 whether house prices after the tornado were different from prices before the tornado and find that they were not, either for the entire sample or for low-income neighborhoods. (See 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 damaged homes following Eq 2. The first set of results, shown in Table 4, considers distance to the nearest damaged home 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 damaged homes 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 increases. In other words, homes within 500 m of a damaged home sell for 16 percent less after the tornado, which is statistically significant. Similar to the 250 meters results, when controlling for the number of damaged homes in this radius, the sale price discount becomes larger (i.e., it is 32 percent). For larger distance radii, e.g., houses within 750 meters of a damaged house, those sold for insignificantly less after the tornado, but when controlling for the number of damaged homes in this range the estimate becomes statistically significant (and it is 27 percent). These findings are similar for the 1000 meters distance band, as the effect is insignificant, but including the number of damaged houses within 1000 meters leads to a statistically significant price discount of approximately 25 percent. Finally, distance bands beyond 1000 meters are statistically insignificant. These results imply that proximity to a damaged home is important in determining the discount, and the discount gradually fades away with less proximity. Houses in neighborhoods with more damaged homes have larger discounts from proximity to those damaged homes.

Table 4: Tornado Impact on House Prices Main Results

	Price (in logs)							
	Within 250 meters		Within 500 meters		Within 750 meters		Within 1000 meters	
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 & # Damaged homes		-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 damaged homes within 250 meters. In this case, in Eq 3 we replace the variable NEAR with the total number of damaged homes. We find each additional damaged home within 250 meters lowers home sale prices by 8 percent. When we consider a larger radius of 500 meters, this discount falls to 2 percent per damaged home, while the effect is smaller for 750 meters. At 1000 meters and beyond, this effect is statistically insignificant. Houses in neighborhoods with more damaged homes have larger discounts from proximity to damaged homes. These results are shown in Table 5.

Table 5: Marginal Effect of an Additional Damaged home

	Price (in logs)			
	Within 250 meters	Within 500 meters	Within 750 meters	Within 1000 meters
Near	-0.0158	0.0504	0.0408	0.0364
	(0.0847)	(0.0771)	(0.0842)	(0.0863)
# of Damaged homes 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 Damaged homes 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. Equation 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 damaged home, as well as the number of damaged homes 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 250 meters		**Within 500 meters**		**Within 750 meters**		**Within 1000 meters**	
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 & # Damaged homes		-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 damaged homes that will be repaired shortly, proxied with the ratio of permits to damaged homes issued within 250 meters, 500 meters, 750 meters, and 1000 meters at the time the house sold following Equation 5. These results, shown in Table 7, are statistically insignificant, and this finding is robust to varying a number of factors. For instance, when we control for the number of damaged homes, the share of permits issued within 250 meters 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 presence of 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 250 meters or 500 meters 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 250 meters			Within 500 meters			Within 750 meters			Within 1000 meters		
Share of permits	**-0.309**	**-0.102**	**-0.281**	**0.206**	**0.262**	**0.329**	**-0.0855**	**0.0739**	**-0.0595**	**0.268**	**0.389**	**0.345**
Near	**(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 & # Damaged homes			-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, is not a significant factor. Perhaps this finding arises due to residents’ expectations that most of the damage is 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 damage.

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 homes to be nonlinear by adding a quadratic term where *Near* x (*Total damaged homes*) indicates the number of damaged homes near the considered home and (*Total damaged homes*)^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 nonlinearities barely affect coefficients and significance from the main specification.

When considering damaged homes within a 500 meters radius of a particular home sale, we also include damaged homes within the 250 meters radius. However, that leads to the question of whether the 500 meters radius results are being driven by the fact that houses between 0 and 250 meters are also included in the 500 meters radius. If one could isolate the effects for damages between 250 meters and 500 meters, for example, that could provide some additional insights into which damaged homes are the most important determinants of the sale prices of nearby houses. As an alternative to the radius approach, we explored distance bands in 250 meters increments—0 to 250 meters, 250 meters to 500 meters, etc.—which leads to the following specification:

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

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

The discount in the 0 to 250 meters band is statistically significant, but the discounts in bands further out are 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 meters) to a damaged home.

Another robustness check that we consider is limiting the sample to post-tornado sales and exploring the marginal effects of additional damaged homes 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 damaged home.

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 housing prices.

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

	Price (in logs)							
	Within 250 meters		Within 500 meters		Within 750 meters		Within 1000 meters	
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 & # Damaged homes		-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. In Table 9, we drop the data in 2024, so that we consider only 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 housing price adjustments are complex and including the entire sample is important for avoiding problems of attenuation bias in the data.

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

	Price (in logs)							
	Within 250 meters		Within 500 meters		Within 750 meters		Within 1000 meters	
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 & # Damaged homes		-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

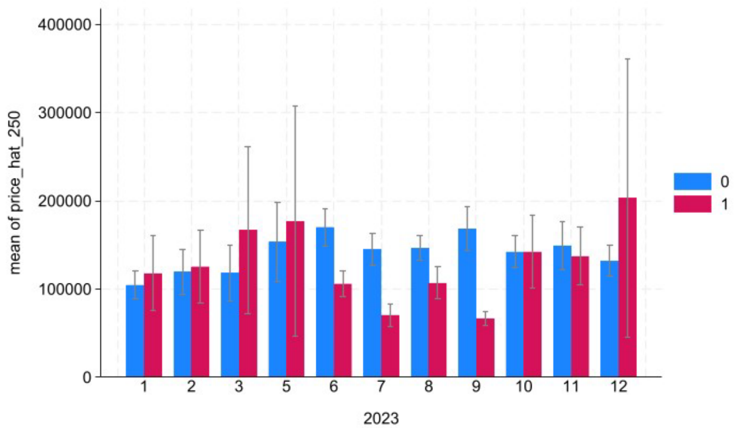
Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

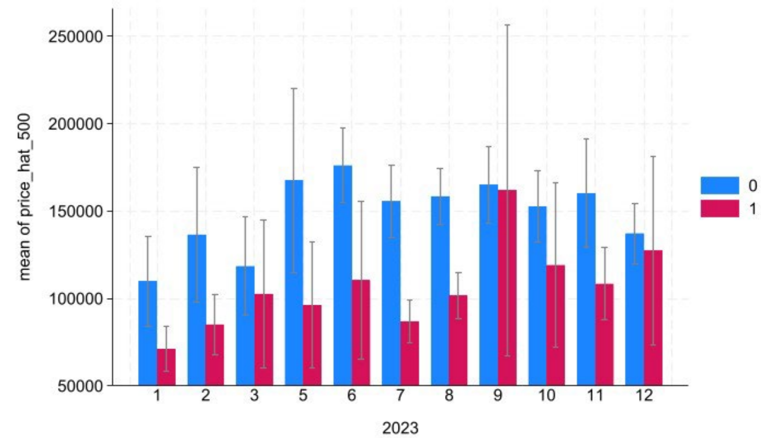
Regressions include house characteristics, block and monthly dummies.

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 housing price trends, month by month, based on the regression estimates of our model in equation 2 (inclusive of the number of damaged homes 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; therefore, the sale date often reflects prices that were determined 45 to 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.

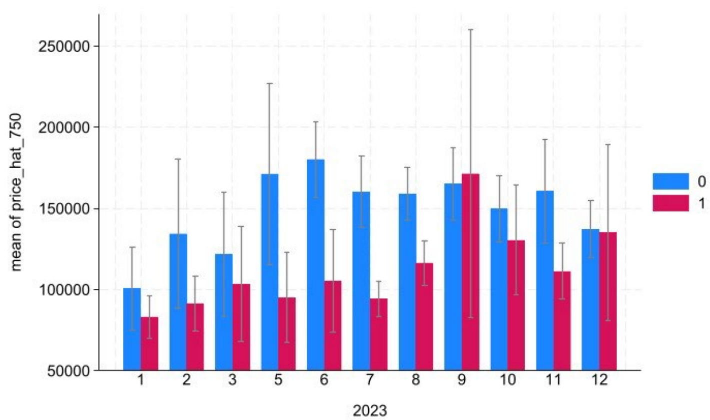
Figure 2 – Parallel Pre-Trends, Various Distance Radii (2023 Months; Tornado Is 3/31/23; April Omitted; May Is within 60 Days of Tornado)



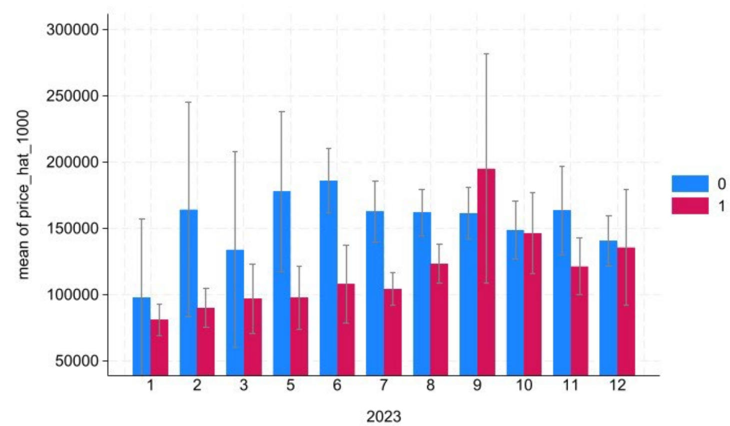
Panel A – Predicted Price for Homes Within 250 meters of a Damaged home



Panel B – Predicted Price for Homes Within 500 meters of a Damaged home



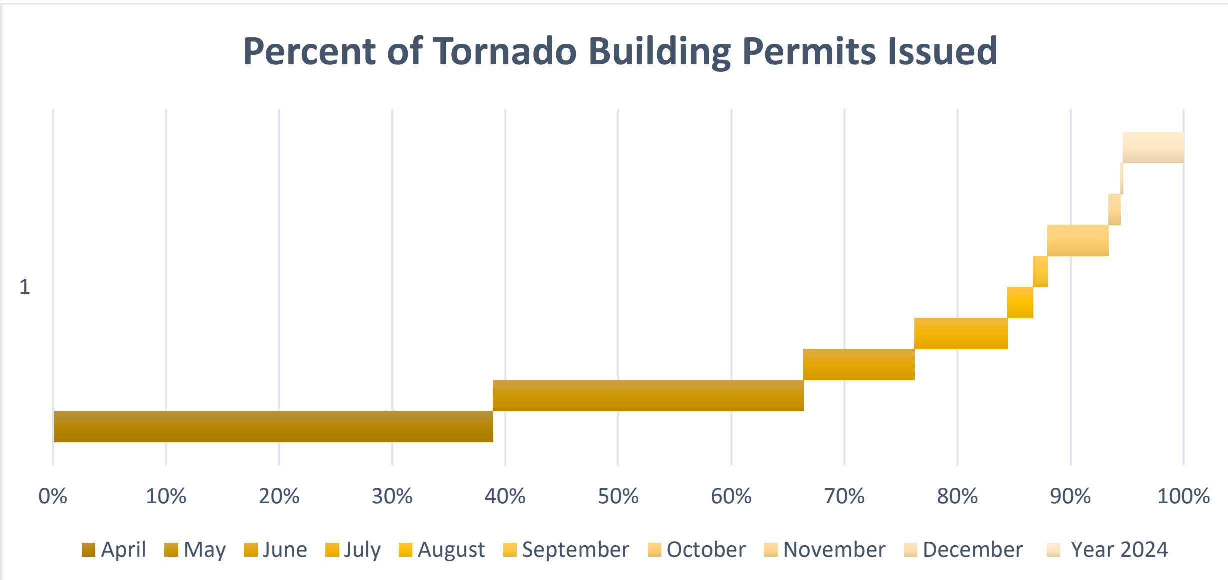
Panel C - Predicted Price for Homes Within 750 meters of a Damaged home



Panel D – Predicted Price for Homes Within 1000 meters of a Damaged home

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 were issued is 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

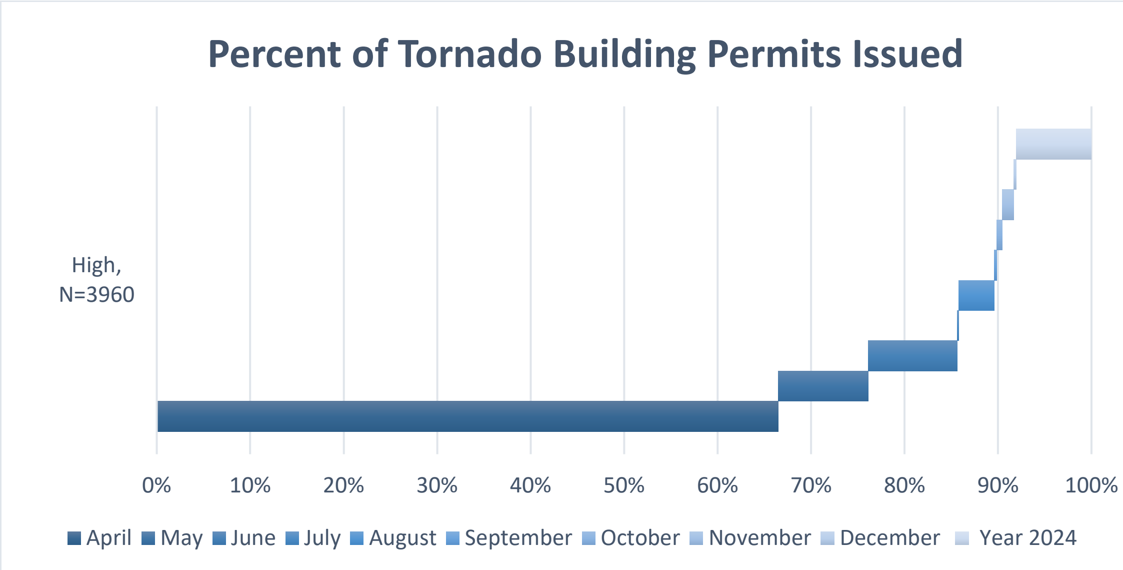
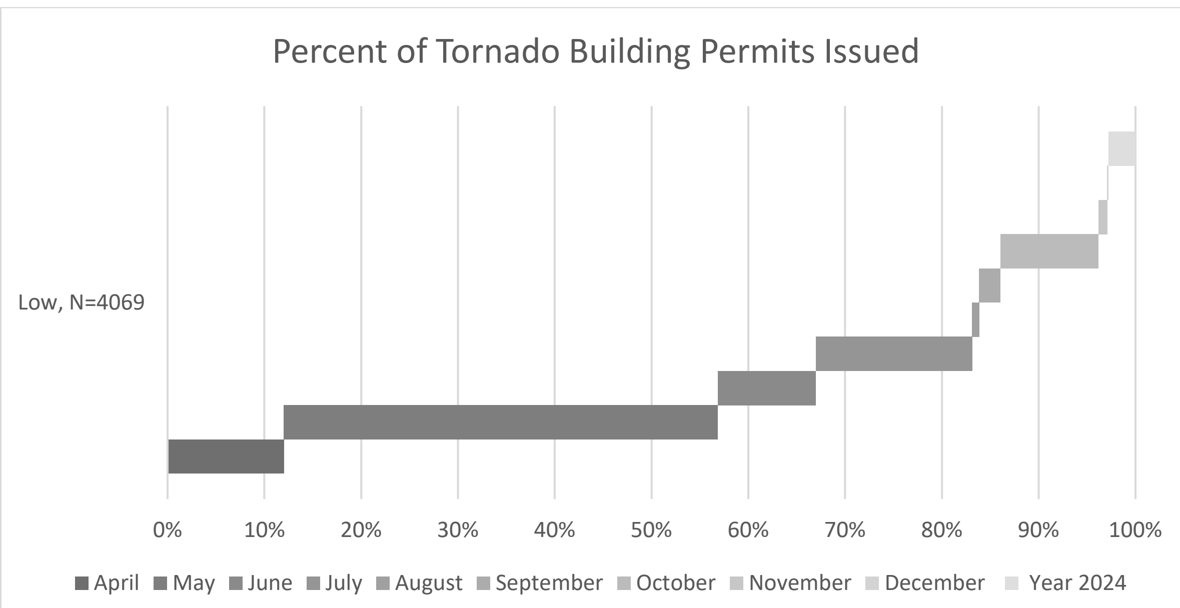


Figure 4b - Cumulative Distribution of Permits Issued Over 2023-24 In "Low" Income Census Tracts



5.Conclusion

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

In this paper, we explore the residential housing price effects of a specific tornado that hit the Little Rock, Arkansas, 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 undamaged home in a neighborhood with damaged properties nearby can lead to capitalization of the overall lower neighborhood quality, because of homeowners' perceptions of worse aesthetics of the neighborhood. We test the hypothesis that undamaged homes that were near damaged ones sold for less than other houses. In addition, we test the hypothesis that the number of nearby damaged homes is a significant determinant of housing 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 statistically significantly evidence of 29 to 35 percent lower residential house prices in neighborhoods within 250 meters of the nearest tornado damaged home, an effect that attenuates as the distance from the nearest damaged home increases. Additionally, there is a 2 to 8 percent price discount for each additional damaged home within 250 meters 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 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 there is a time lag between when the permit information becomes publicly available and the dates of the initiation of the permit process, and 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 funding policy related to tornado damage cleanup. 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 if surrounding damaged homes were not be repaired and ended up vacant. Nevertheless, this paper finds that these neighborhoods were not additionally impacted—potentially 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 housing 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 location of damaged homes impacts housing prices can also be important information for (i) policy makers considering how and where to allocate recovery funds and (ii) investors who purchase housings. 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 damaged home proximity on housing prices was larger or smaller than what we found for Little Rock. This could have further implications for where to direct cleanup funds: 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 housing prices change differently for various natural disasters can allow for an important comparison of how to direct such aid depending on the type of disaster.

References

Cho, W., Whitacre, B. E., & Rhoades, C. A. (2022). The Effects of Tornadoes on Housing Prices in Moore, Oklahoma. *Review of Regional Studies*, *52*(1), 57-73.

Cohen, J. P., Barr, J., & Kim, E. (2021). Storm surges, informational shocks, and the price of urban real estate: An application to the case of Hurricane Sandy. *Regional Science and Urban Economics*, *90*, 103694

Cohen, J. P., Coughlin, C. C., Crews, J., & Ross, S. L. (2023). Longer term housing market effects of a major US airport closure. *Real Estate Economics*, *51*(4), 990-1010.

Contat, J., Hopkins, C., Mejia, L., & Suandi, M. (2024). When climate meets real estate: A survey of the literature. *Real Estate Economics*.

Donadelli, M., Jüppner, M., Paradiso, A., & Ghisletti, M. (2020). Tornado activity, house prices, and stock returns. *The North American Journal of Economics and Finance*, *52*, 101162.

Ewing, B. T., Kruse, J. B., & Wang, Y. (2007). Local housing price index analysis in wind-disaster-prone areas. *Natural Hazards*, *40*, 463-483.

Feng, P., Zhou, Z., Cohen, J. P., & Yasar, M. (2024). Air pollution and the effects on house prices: A push for sustainability. *Journal of Real Estate Research*, 1-24

Gallagher, J., Hartley, D., & Rohlin, S. (2023). Weathering an unexpected financial shock: the role of federal disaster assistance on household finance and business survival. *Journal of the Association of Environmental and Resource Economists*, *10*(2), 525-567.

Gatzlaff, D., McCullough, K., Medders, L., & Nyce, C. M. (2018). The impact of hurricane mitigation features and inspection information on house prices. *The Journal of Real Estate Finance and Economics*, *57*, 566-591.

Johnson, E. B., Tidwell, A., & Villupuram, S. V. (2020). Valuing curb appeal. *The Journal of Real Estate Finance and Economics*, *60*, 111-133.

Roth Tran, Brigitte, Daniel J. Wilson. 2023. "The Local Economic Impact of Natural Disasters," Federal Reserve Bank of San Francisco Working Paper 2020-34. https://doi.org/10.24148/wp2020-34

Sutter, D., & Poitras, M. (2010). Do people respond to low probability risks? Evidence from tornado risk and manufactured homes. *Journal of Risk and Uncertainty*, *40*, 181-196.

Yi, D., & Choi, H. (2020). Housing market response to new flood risk information and the impact on poor tenant. *The Journal of Real Estate Finance and Economics*, *61*(1), 55-79.

Zhao, D., & Grinstein-Weiss, M. (2021). Do Near Misses With a Disaster Affect Individual Demand for Credit? A Large-Scale Study of Credit Profiles. *A Large-Scale Study of Credit Profiles (December 18, 2021)*.

Appendix

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

	Average number of total damaged homes		Median number of total damaged homes	
	Low Income	High Income	Low Income	High Income
Within 250 meters	3.2	4.5	1	3
Within 500 meters	7.4	7.7	5	8
Within 750 meters	11.0	11.3	6	10
Within 1000 meters	14.4	14.5	8	10

Table A2: Number of homes sold near damaged homes

		Pre-Tornado	**Post-Tornado**
Within 250 meters	High	33	57
	Low	53	39
Within 500 meters	High	60	110
	Low	106	86
Within 750 meters	High	91	153
	Low	134	124
Within 1000 meters	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 homes

	Price (in logs)			
	Within 250 meters	Within 500 meters	Within 750 meters	Within 1000 meters
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 & # Damaged homes	-0.0649	-0.00867	-0.00997	0.000103
	(0.0515)	(0.0150)	(0.0148)	(0.0119)
# Damaged homes 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)			
	0 meters - 250 meters band	**250meters - 500 meters band**	**500 meters - 750 meters band**	**750 meters – 1000 meters band**
Post_tornado	-0.0370	-0.0771	-0.0838	-0.0839
	(0.285)	(0.275)	(0.269)	(0.269)
Band	0.189	0.163*	-0.0305	-0.0788
	(0.127)	(0.0844)	(0.106)	(0.157)
Band x Post_tornado	-0.264**	-0.00785	0.0731	0.125
	(0.105)	(0.113)	(0.139)	(0.174)
# damaged homes in 0-250 meters	-0.0647			
	(0.0495)			
# damaged homes in 250 meters-500 meters		0.00458		
		(0.00896)		
# damaged homes 500-750 meters			-0.00178	
			(0.00563)	
# damaged homes 750-1000 meters				0.00164
				(0.00513)
Constant	12.04***	12.05***	12.03***	12.03***
	(0.218)	(0.219)	(0.218)	(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.