Housing Beyond the Path of Destruction: Market and Neighborhood Spillovers from a St. Louis Tornado

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April 2026

Abstract: While the economic toll of natural disasters is typically measured by direct physical destruction, this paper investigates the severe neighborhood spillovers imposed on undamaged properties. Exploiting the highly localized damage corridor of the May 2025 St. Louis tornado, we evaluate its causal impact on housing prices, transaction volume, and vacancies, for undamaged residential parcels. Using a difference-in-differences framework, we identify a dual-channel mechanism of neighborhood distress. First, through a rapid capitalization channel, undamaged homes within 250 meters of the damage path suffered transaction price declines of 20 percent or more relative to control properties. This discount is highly localized, concentrated primarily within the first 100 meters. Second, utilizing probabilistic vacancy data, we uncover a delayed displacement channel. Specifically, while price adjustments were rapid, significant spikes in new property vacancies did not emerge until several months post-disaster. While the relative price spillovers were uniform across demographic groups, the absolute burden fell heavily on low-income neighborhoods. Finally, this paper makes a novel contribution by isolating a compounding institutional shock from the tornado-induced closure of two local elementary schools. Applying Inverse Probability Weighting (IPW) to balance school attendance zones, we demonstrate that the destruction of institutional anchors may amplify the negative physical externalities of the storm. Ultimately, our findings may imply that disaster recovery policies extending beyond rebuilding damaged structures to include targeted "buffer zone" stabilization and institutional restoration could prevent post-disaster vacancy contagion and urban blight.

JEL Codes: R21, R31, Q54, H84

Keywords: natural disasters, tornadoes, housing markets, difference-in-differences, urban externalities, vacancy, spillovers, school closures, inverse probability weighting

Disclosures: The views in this paper are those of the authors and not necessarily representative of the Federal Reserve Bank of St. Louis, the Federal Reserve System, or the Federal Reserve Board. The authors have no conflicts of interest to declare.

1. Introduction

On May 15, 2025, a severe convective storm system produced a tornado that traversed several neighborhoods in north St. Louis. The tornado intensified from EF1 to low-end EF3 strength along its path, causing an estimated $1.6 billion in property damage, five fatalities, and damaging hundreds of structures. While the most visible impacts were concentrated among directly damaged properties, disasters of this kind may also generate broader neighborhood spillovers through displacement, neighborhood disamenities, and changes in perceived risk.

This paper examines how the St. Louis tornado affected nearby undamaged residential properties. We study whether proximity to tornado damage altered housing prices, sales activity, and vacancy patterns among properties that were not themselves physically damaged. Crucially, the tornado also generated an additional institutional shock: the closure of Ashland and Hickey Elementary Schools. Because school attendance zones are capitalized into housing markets, disruption to local school access may amplify housing market spillovers beyond the direct effects of nearby damage.

Tornadoes provide a useful setting for studying localized housing market spillovers because they generate highly concentrated physical destruction along a narrow and largely unpredictable path. This spatial randomness allows researchers to compare properties located very near the damage corridor to otherwise similar properties located slightly farther away within the same urban environment. St. Louis is a particularly compelling setting given its pronounced neighborhood-level heterogeneity in housing market strength, population trends, and economic resilience.

We exploit this spatial variation using a difference-in-differences framework. Our primary treatment group consists of undamaged residential parcels located within 250 meters of tornado-damaged properties. We compare outcomes during the March–December period of 2025 with the same seasonal window in 2024, thereby controlling for strong seasonal patterns in housing transactions and vacancy dynamics. We restrict analysis to parcels north of the Lindell–Forsyth corridor, the relevant urban submarket affected by the storm.

Our analysis contributes to a growing literature, in four ways. First, we provide parcel-level evidence on disaster spillovers at meter-scale resolution. Second, we jointly analyze prices, sales volume, and vacancy, enabling us to distinguish a rapid capitalization channel from a slower displacement channel. Third, we exploit school closure as a secondary treatment dimension, using inverse probability weighting at the zone level. Fourth, we document distance gradients showing that effects are highly localized within 100–250 meters of damage.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data and the workflow used to construct the analytical sample. Section 4 presents the empirical strategy. Section 5 reports results. Section 6 presents robustness checks. Section 7 concludes.

2. Literature

There is a significant literature on natural disasters and property prices. The hedonic pricing literature establishes that house characteristics are capitalized into house prices (Rosen, 1974). More recent literature, such as Cohen et al. (2021) and Cohen and Gutkowski (2026) have demonstrated that proximity to natural hazards can be considered as a characteristic that is capitalized into housing prices. For instance, Cohen, Barr, and Kim (2021) study Hurricane Sandy and document how informational shocks from storm surges propagate into urban real estate prices.

In related earlier literature, Bin and Polasky (2004) find floodplain designation reduces home values (opposed to prices), while Hallstrom and Smith (2005) exploit a near-miss hurricane to estimate option-value losses. Bakkensen and Barrage (2021) document price effects of flood risk disclosure. More recently, Zivin, Liao, and Panassie (2023) show how hurricanes reshape housing markets in Florida, finding persistent capitalization effects that vary with storm intensity.

There is also a smaller but important literature on post-disaster market dynamics and tornadoes. For instance, Cho, Whitacre, and Rhoades (2022) examine housing price effects of tornadoes in Moore, Oklahoma, finding that proximity to prior tornado paths reduces home values by 2 to 5 percent in the year following a storm, with effects dissipating thereafter. Donadelli et al. (2020) document a negative correlation between tornado activity and home prices at the MSA level. Ewing, Kruse, and Wang (2007) estimate that tornado-related losses can reach up to two percent of total local housing stock value. Gatzlaff et al. (2018) document positive price effects of tornado shelters, capturing the mitigation value of preparedness investments.

The closest antecedent to the present paper is Cohen and Gutkowski (2026), who study the effects of the March 2023 Little Rock, Arkansas tornado on undamaged single-family home prices, finding approximately a 20 percent discount for properties within 250 meters of damage. This effect is transitory, however, since these price effects are present in the first 9 months following the tornado but subsequently return to their pre-tornado levels.

Other recent papers study financial factors related to tornados, opposed to property prices. For instance, Gallagher, Hartley, and Rohlin (2023) examine credit and migration outcomes following tornadoes, finding that disaster aid shapes household balance sheets and migration patterns. Roth Tran and Wilson (2023) document increases in per-capita income in tornado-affected areas, reflecting rebuilding activity. Sutter and Poitras (2010) study manufactured housing vulnerability, finding that low-probability risk perceptions influence location decisions.

Despite the broad range of focal areas of previous tornado studies, there are some important variables that have not been closely considered, especially as tornadoes relate to urban neighborhood decline. Kallberg and Shimizu (2025) document joint dynamics of crime and housing prices, motivating attention to broader neighborhood disruption channels following disaster shocks. Another important variable is the extent of vacancies in urban areas following a tornado opposed to beforehand. Vacancy is an understudied outcome in the disaster literature despite its central role in neighborhood stabilization theory (Sampson, 2012). Our parcel-level probabilistic vacancy dataset, when merged with our data on the path of the tornado and locations of damage points in St. Louis, enables us to test whether disasters accelerate vacancy in surrounding areas and whether these effects are delayed relative to price responses.

3. Data

The geographic focus of this study is on properties in the City of St. Louis, Missouri. Our analysis is restricted to residential parcels located north of the Lindell Boulevard–Forsyth Boulevard corridor.[1] This boundary defines the relevant urban submarket affected by the storm and excludes the central business district and south city neighborhoods where housing market dynamics differ

[1] This boundary corresponds to approximately 38.638°N latitude, or y ≈ 4,666,500 in EPSG:3857.

substantially. All filters, including damage classification, treatment assignment, vacancy linkage, and figure extents, are applied uniformly within this geographic boundary.

Our primary dataset is a parcel-level property file for St. Louis City covering all residential parcels. The parcel file includes sales records. We restrict analysis to residential properties with positive assessed market values, and arms-length transactions. While some properties that are classified as arms-length transactions have sales prices of $0, this is not uncommon for this neighborhood in St. Louis as some homeowners in these severely blighted neighborhoods are eager to unload properties to avoid having to pay property taxes on homes that are uninhabitable, even before the tornado. For robustness, we also perform some analyses using a cutoff of $1,000 for the lower-bound of sales prices, and again a separate analysis with a lower-bound of $5,000.

Tornado damage is identified from two independent sources: the National Weather Service storm damage survey (465 parcels) and the City of St. Louis emergency assistance registry. Because the city aid program operates citywide, the raw registry flags approximately 22,450 residential parcels. We retain city-aid records only for parcels located within 500 meters of the NWS tornado path centerline and north of the Lindell–Forsyth boundary, yielding approximately 6,464 city-aid parcels within the confirmed corridor. Figure 1 below shows the tornado path and the damage points as recorded by the alternative sources.

Our composite damage indicator equals one if a parcel is identified as damaged by either source: the NWS survey or the spatially filtered city assistance registry. This yields approximately 6,929 damaged parcels in total. The 500-meter threshold corresponds roughly to the half-width of the storm at peak intensity, as reported by the NWS survey (maximum width 1,750 yards). Robustness checks use the NWS survey alone as an alternative damage definition.

Home sales are observed from recording dates during March–December in each year. We restrict the analysis to 2024 and 2025. The post indicator equals one for any sale recorded on or after May 15, 2025 (the tornado date) and zero otherwise. With approximately 950 non-zero priced post-tornado sales and 400 arms-length sales of undamaged homes post-tornado, confidence intervals are expected to be wide; we emphasize coefficient magnitude and direction alongside statistical significance.

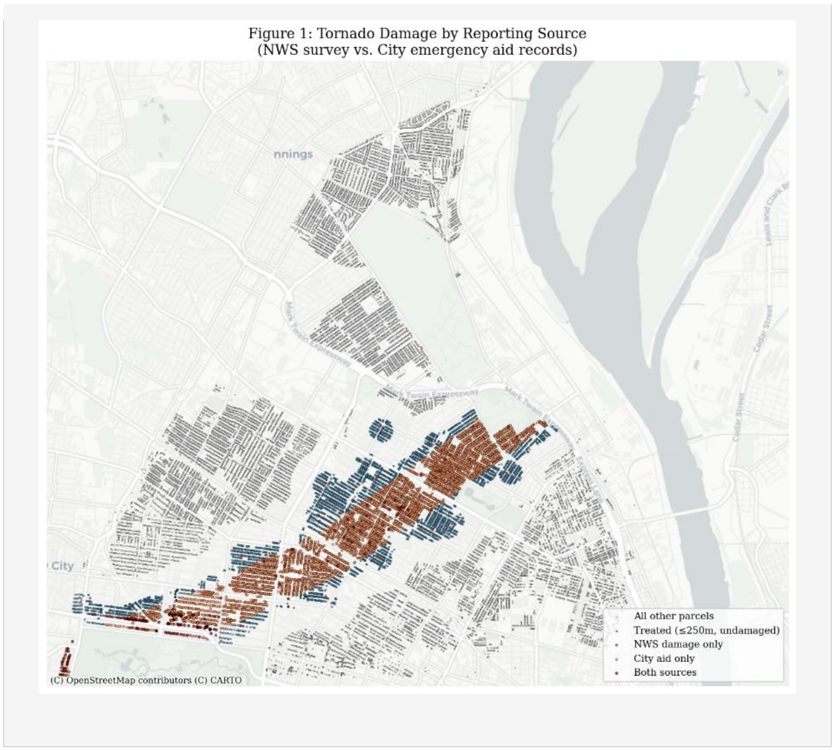

Figure 1: *Tornado Damage by Reporting Source*

Note: Parcels identified as damaged by NWS survey only (red), city aid only within 500m of path (orange), and both sources (dark red). Treated parcels (undamaged, ≤250m) shown in blue. Restricted to north of Lindell–Forsyth boundary.

Another important aspect of the tornado in St. Louis, which has not been extensively explored in the tornadoes literature, is the relationship between vacant homes and proximity to damaged homes. We use a probabilistic vacancy dataset, derived from the information available at stlvacancytools.com, retaining observations with a vacancy likelihood score of 75 or above (where the maximum possible value is 100 and the lowest is 0). Vacancy records are linked to parcels using a two-stage procedure: exact address matching (street number and name) in the first stage, and nearest-neighbor spatial matching within 50 meters in the second stage. We construct vacancy change measures for March–December (primary) and September–December (lagged) windows. A June–August window captures the immediate post-tornado period for distance gradient analysis.

We also merge in the 2019–2023 ACS 5-year estimates for St. Louis City (state FIPS 29, county FIPS 510) including tract-level median household income, percent bachelor's degree or higher, percent Black or African American, percent owner-occupied, and poverty rate. All 59,775 residential parcels north of the I-64 highway boundary match to an ACS tract record.

Finally, we merge in data that enable us to consider elementary school attendance zones that had a school that closed, and others that had at least one damage point in the zone from the tornado. Two schools — Ashland and Hickey Elementary — were closed following the tornado. Parcels are assigned to closed or open attendance zones using a prepared-geometry point-in-polygon test. We build a tract-level pre-tornado vacancy rate variable (any vacancy in 2024 per tract) for use as an additional control in a DiD event study with full controls.

4. Empirical Strategy

Our primary (baseline) identification strategy is a difference-in-differences framework exploiting the spatial discontinuity created by the tornado's damage corridor. We compare outcomes for undamaged residential parcels located within 250 meters[2] of a damaged parcel (treated) to undamaged parcels located farther away (control), before and after the tornado. One set of outcomes we explore are sale prices of undamaged homes. The other outcomes we consider are the likelihood of a property being vacant. Therefore, we have two separate sets of empirical analyses. Generally speaking, the estimating equation for each of these outcomes (Y_{it}) is:

$$Y_{it} = \beta(NearDamage_i \times Post_t) + \gamma NearDamage_i + \delta Post_t + X_i\theta + \mu\_n + \varepsilon_{it}$$

where $NearDamage_i$ equals one for undamaged parcels within 250 meters of damage, $Post_t$ equals one for observations on or after May 15, 2025, X_i is a vector of parcel controls (building area, year built, assessed market value, bathroom count), and μ_n are neighborhood fixed effects. Standard errors are heteroskedasticity-robust (HC1) throughout.

We additionally construct mutually exclusive distance ring dummies (0–100m, 100–250m, 250–500m, 500–750m) to document the distance gradient.

To assess parallel trends and trace the timing of effects, we estimate a monthly event study DiD for the price outcome variable. The control group is restricted to undamaged parcels more than 750 meters from damage (to ensure a clean control). The specification includes building square footage, year built, tract-level pre-tornado vacancy rate, median household income, percent Black,

[2] Treatment distance is computed as Euclidean distance from each parcel centroid to the nearest damaged parcel centroid in EPSG:3857, recomputed from the corrected composite damage definition rather than relying on pre-existing binary flags in the source data.

poverty rate, percent owner-occupied, and percent with a bachelor's degree as covariates, in addition to neighborhood fixed effects. The reference period is April 2025 (one month before the tornado). The sample is restricted to May–December in each year.

Separately, the vacancy DiD uses the full March–December window. A secondary specification isolates September–December to capture the lagged displacement channel. Figure 6 normalizes vacancy changes by the pre-June 2024 vacancy rate per distance band, providing a measure of the proportional increase relative to the pre-tornado baseline.

Finally, to test whether school closure amplified housing market disruption, we estimate a separate DiD comparing undamaged parcels in Ashland and Hickey attendance zones (treatment) to undamaged parcels in all other St. Louis elementary school zones (control). Propensity scores are estimated at the school zone level using logistic regression on seven balancing variables: ACS demographics and 2024 pre-period housing outcomes. Stabilized Inverse Probability Weights (IPW) are trimmed at the 99th percentile and normalized within each group. The weighted DiD uses Weighted Least Squares (WLS) with HC1 standard errors.

5. Results

Table 1a presents descriptive statistics for all residential parcels north of the Lindell–Forsyth corridor (38.64°N). The sample includes 44,536 parcels with positive assessed market values. The typical parcel has an assessed value of approximately $77,000 (median $14,209), a building footprint of 1,838 square feet, and was built around 1920. Treated parcels (undamaged, ≤250m of damage) have modestly larger structures (1,991 vs. 1,768 sq ft) and slightly higher assessed values ($83,100 vs. $68,269) than controls.

Among arms-length sales (price > $10,000, March–December), the pre-tornado mean sale price was $266,091 for the full sample (median $90,000). Among treated parcels, the pre-tornado mean was $186,229 (median $88,500), compared to $274,741 (median $91,250) for controls. Total arms-length sales were 1,769: 1,146 pre-tornado and 623 post-tornado. Hence, while the treated parcels have a slightly lower assessed price, their sale price was significantly lower, while maintaining similar characteristics.

Table 1a: Descriptive Statistics

Variable	All Mean	All Median	N	Treated Mean	Treated Median	Control Mean	Control Median
Assessed market value ($)	77,142	14,209	44,536	83,100	14,784	68,269	13,911
Building sq ft	1,838	1,536	37,546	1,991	1,746	1,768	1,410
Lot acres	0.3	0.1	2,090	0.2	0.1	0.3	0.1
Year built	1,920	1,912	37,594	1,914	1,910	1,923	1,914
Stories	1.8	2.0	34,156	1.9	2.0	1.7	2.0
Bathrooms	1.2	1.0	33,213	1.2	1.0	1.2	1.0
Pre-tornado sale price ($)	266,091	90,000	1,146	186,229	88,500	274,741	91,250
Post-tornado sale price ($)†	1,883,140	90,000	623	221,420	50,000	2,149,263	93,000

Note: Treated = undamaged parcels ≤250m from damage. Control = all other undamaged parcels. Pre = March–December 2024; Post = May 15–December 2025. † Post mean inflated by outlier transactions ≥1,000m from damage; median is more representative.

Table 1b presents the pre-tornado balance table. Building area, assessed values, and median household income are statistically indistinguishable across groups. However, year built and stories show small, marginally significant, differences. Poverty rate and owner-occupancy also differ statistically, but are economically modest and absorbed by neighborhood fixed effects in the regressions. We conclude the samples are broadly comparable prior to the tornado.

Table 1b: Balance Table — Pre-Tornado Characteristics

Variable	Treated Mean	Control Mean	Treated N	Control N	p-value
Building area (sq ft)	2,100	1,864	112	1,034	0.114
Year built	1,919	1,926	112	1,001	0.007**
Assessed market value ($)	114,324	136,224	112	1,034	0.388
Value of improvements ($)	107,030	128,468	112	1,034	0.373
Land value ($)	7,294	7,755	112	1,034	0.771
Stories	1.97	1.80	112	1,034	0.012*
Median household income ($)	44,775	45,267	112	1,034	0.648
% Black or African American	76.2	71.8	112	1,034	0.122
Poverty rate (%)	23.4	26.2	112	1,034	0.001***
% Owner-occupied (%)	48.0	42.9	112	1,034	<0.001***

*Note: Pre-tornado sample (post = 0) only. Welch two-sample t-tests. *** p<0.01, ** p<0.05, * p<0.10.*

Table 2 presents differences-in-differences estimates for log sale price. Across all four specifications, treated properties experienced statistically significant price declines of 24–33 log points (~21–28 percent) relative to controls following the tornado. In the most parsimonious specification (1) the estimate is −0.325. Adding neighborhood fixed effects yields −0.241. Including ACS tract controls raises the estimate to −0.297, and is unchanged when year fixed effects are added. The stability across specifications confirms the result is not driven by compositional changes in sold properties.

Table 2: DiD — Log Sale Price

	(1) No FE	(2) Nbhd FE	(3) Nbhd FE + ACS	(4) Nbhd + Year FE + ACS
NearDamage × Post	−0.325**	−0.241**	−0.297***	−0.296***
	(0.137)	(0.109)	(0.112)	(0.112)
Property controls	Yes	Yes	Yes	Yes
Neighborhood FE	No	Yes	Yes	Yes
ACS tract controls	No	No	Yes	Yes
Year FE	No	No	No	Yes
Observations	1,707	1,707	1,706	1,706
R^2	0.445	0.657	0.675	0.675

*Note: Dependent variable: log sale price. Arms-length sales, price > $10,000, March–December 2024 and 2025. Property controls: building area, year built, assessed market value, bathroom count. ACS controls: median HH income, % Black, poverty rate, % owner-occupied. HC1 robust SEs in parentheses. *** p<0.01, ** p<0.05.*

The key coefficient is the interaction of NearDamage and Post. We explore a set of ring-specific DiD coefficients, with results shown in Table 3. Effects are significant and negative in the 0–100m ring, and attenuate with distance. Specifically, the estimated coefficient for houses between 0 and 100 meters from a damaged home is approximately -0.48 and statistically significantly less than zero (at less than the 0.05 level), implying a major drop in price in close proximity. All of the other distance ring estimates, including 100-250 meters, 250 to 500 meters, and 500 to 750 meters, are statistically insignificant. Given approximately 400 arms-length sales of undamaged homes in the post period, confidence intervals are correspondingly wide. Therefore, we emphasize the direction and economic magnitude of the estimates.

Table 3: Distance Ring Heterogeneity — Log Sale Price

Distance Ring	Coefficient	Std. Error	p-value	Sig.	Sales (N)
0–100m	−0.501	0.168	0.003	***	58
100–250m	−0.225	0.135	0.097	*	141
250–500m	0.089	0.140	0.522		152
500–750m	0.000	0.146	0.997		123

*Note: Ring × Post DiD. Property controls and neighborhood FE included. HC1 robust SEs. *** p<0.01, * p<0.10.*

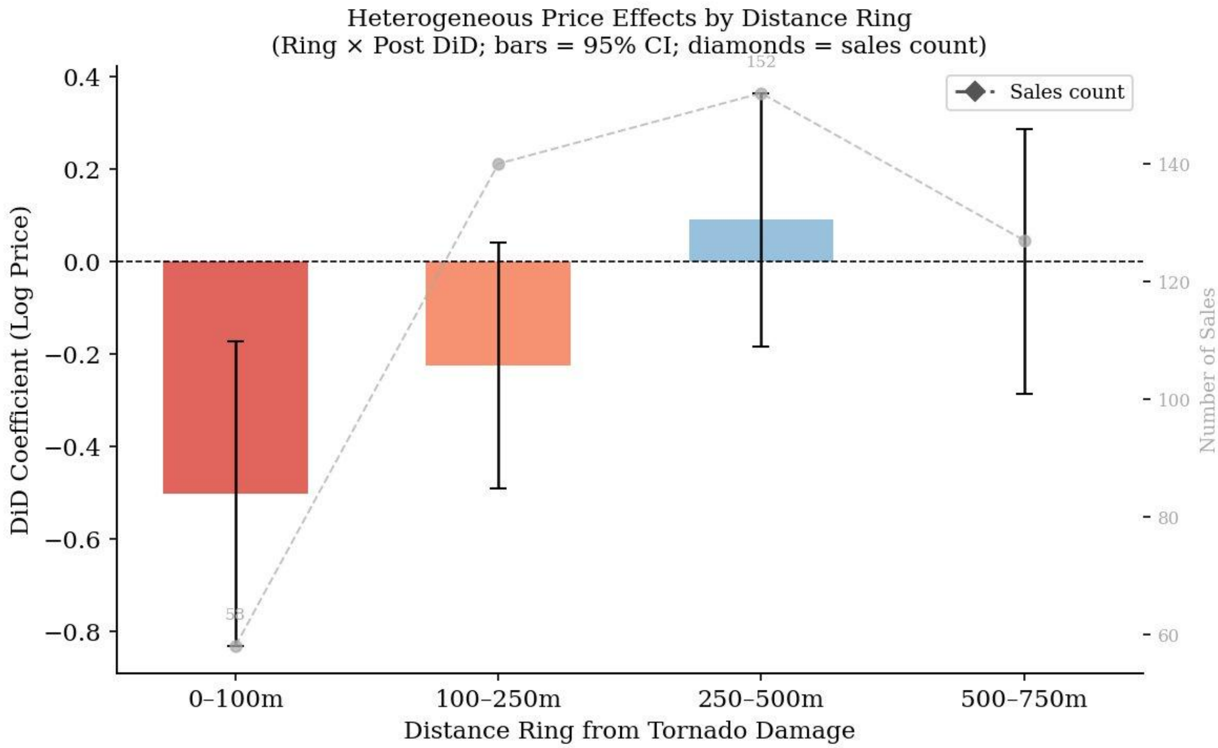

Figure 2: Heterogeneous Price Effects by Distance Ring. Bars = 95% CI. Secondary axis (gray) = sales count per ring.

Figure 3 shows the DiD treatment effect coefficients by distance ring, along with the number of sales (which is on the right-hand scale). The 0 to 100m distance ring has the fewest number of sales but is the only band that has a significantly negative treatment effect estimate. When moving to rings that are further out from the nearest damage point, the number of sales is increasing, until 500m, at which point there is a slight decline in the number of sales.

Next we explore the density of residential sales, before and after the tornado. Figure 3 shows kernel density estimates of residential sales for June–December 2024 (n = 627, left) and June–December 2025 (n = 590, right). Sales density around the damage path appears broadly similar across periods, with no obvious spatial withdrawal post-tornado. Table 4 confirms this visual analysis: the LPM yields a small positive and marginally significant treatment effect of 0.007, suggesting treated parcels were slightly more likely to transact post-tornado, possibly reflecting distressed selling or investor acquisitions.

Table 4: DiD — Probability of Sale (LPM)

	(1) No FE	(2) Nbhd FE	(3) Nbhd FE + ACS
NearDamage × Post	0.0072*	0.0072*	0.0073*
	(0.0039)	(0.0039)	(0.0039)
Property controls	Yes	Yes	Yes
Neighborhood FE	No	Yes	Yes
ACS tract controls	No	No	Yes
Observations	75,188	75,188	75,170

*Note: Dependent variable: indicator for arms-length sale (price > $10,000) in the March–December window. Parcel-year panel, 2024 and 2025. NearDamage is an indicator for whether each home sales observation was within 250 meters from the nearest damage point. HC1 robust SEs in parentheses. * p<0.10.*

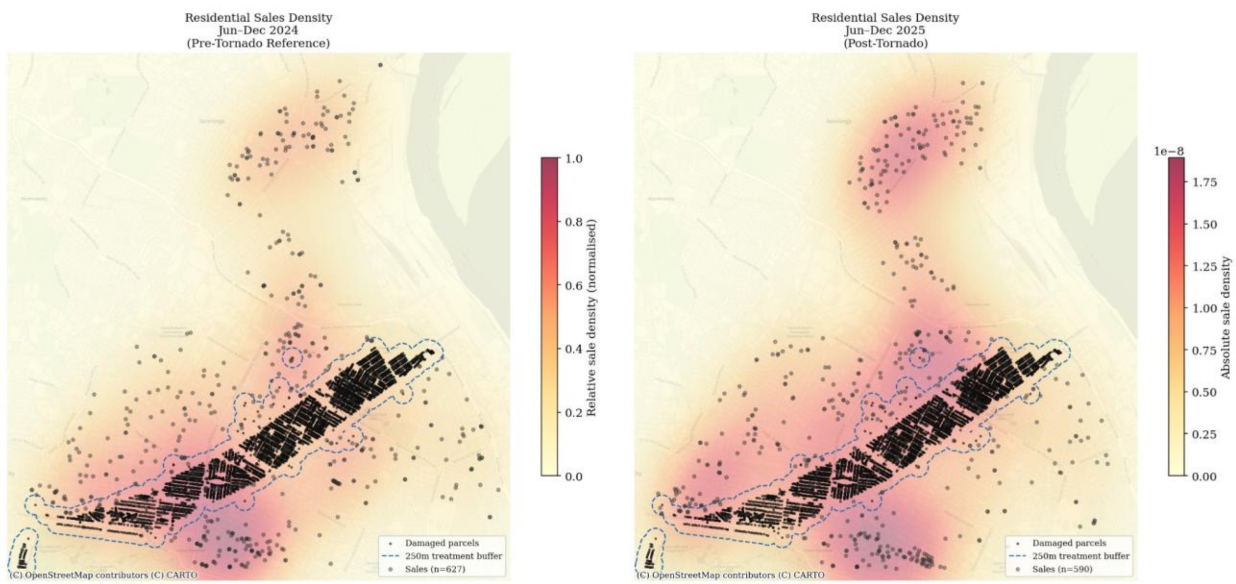

Figure 3: Residential Sales Density — Jun–Dec 2024 (left, normalised) vs. Jun–Dec 2025 (right, absolute). Dashed blue = 250m treatment buffer. Dark dots = damaged parcels.

Figure 4 presents vacancy density estimates from 2024 (in shaded colors of yellow, orange and brown), for the June to August 2025 period (left panel) and September to December 2025 period (right panel). It is noteworthy that for the 250 meters boundary from the nearest tornado damage point, the prevalence of vacancies seems to be greater, and scattered along this boundary line, in the September to December period. This pattern is less apparent for the first few months following the tornado in the left panel. This finding is consistent with the result from the DiD sale price regression that price declines in the treated areas did not start showing up until around December 2025. This timing synergy between delayed price capitalization and lagged vacancy onset near damage points suggests two distinct channels for the effects on housing markets.

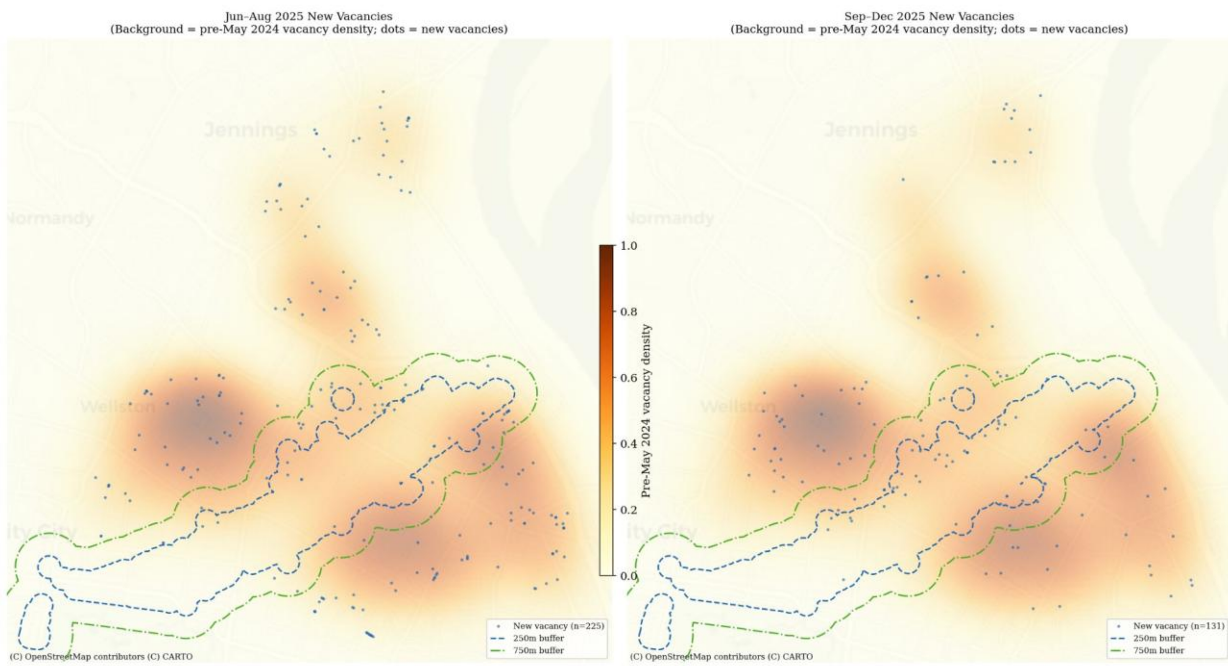

Figure 4: New Vacancy Onset. Background = pre-May 2024 vacancy density (same both panels). Blue dots = new vacancies. Left: Jun–Aug 2025 (n=225); Right: Sep–Dec 2025 (n=131). Dashed blue = 250m buffer; dash-dot green = 750m buffer.

Table 5 formalizes this timing. The March–December full-window coefficient is 0.0023 (SE = 0.0022, p = 0.293), which is not significant. The September–December lagged coefficient is 0.0033 (SE = 0.0016, p = 0.040), which is significant at 5 percent. The timing match between delayed price effects (deepening through December 2025 in the event study) and lagged vacancy onset suggests two connected channels: rapid price discounting and slower displacement.

Table 5: Vacancy DiD — New Vacancy Onset

Window	Coefficient	Std. Error	p-value	Sig.	N
Mar–Dec 2025 (full window)	0.0023	0.0022	0.293		31,701
Sep–Dec 2025 (lagged window)	0.0033	0.0016	0.040	**	31,701

*Note: Dependent variable: vac_onset = 1 if parcel first appears in vacancy registry in the 2025 window and was absent in the corresponding 2024 window. Property controls and neighborhood FE included. HC1 robust SEs. ** p<0.05.*

Another perspective on the vacancies patterns after the tornado is with the distance gradient. Figure 5 shows the normalized vacancy gradient by distance band, with confidence intervals (95%) and sample size (n) labels shown within bars. Vacancy gradients by distance band are shown for the June to August period (left panel) and separately for the September to December period (right panel). In all bands for the June to August period, the vacancies are significantly higher in 2025 than in 2024. For the September to December period, the vacancies are barely significantly higher in the 500m to 750m band, and they are noticeably higher in the other bands.

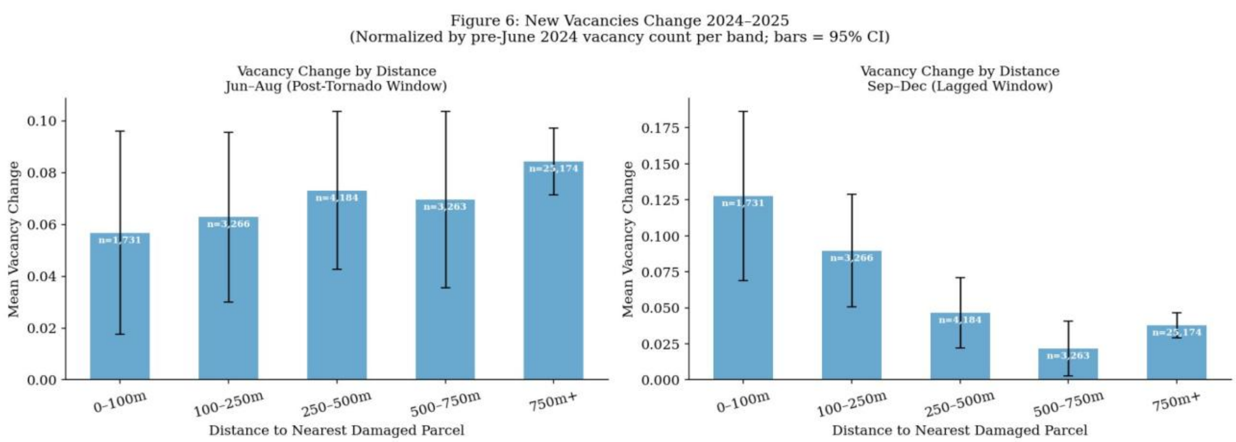

Figure 5: Normalized Vacancy Gradient by Distance Band. Mean new vacancy onset per band normalized by pre-June 2024 baseline rate. Left: Jun–Aug 2025; Right: Sep–Dec 2025. Error bars = 95% CI.

Next, we explore price changes due to the tornado. Figure 6 plots monthly log price changes for treated parcels relative to April 2025. Pre-period coefficients (May–December 2024) oscillate around zero and the joint pre-trend F-test is $F = 1.462$ ($p = 0.132$), confirming parallel trends. Post-tornado coefficients are consistently negative and deepen through December 2025 (≈ -0.65 log points).

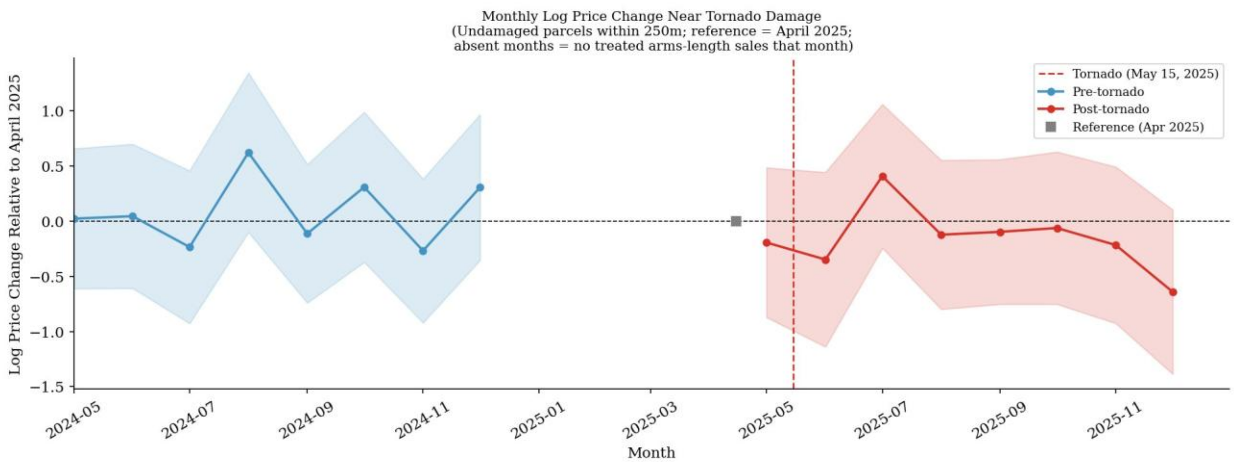

Figure 6: Monthly Log Price Change Near Tornado Damage. Within-treated event study. Treated = undamaged parcels ≤250m. Blue = May–Dec 2024 (pre); Red = May–Dec 2025 (post). Shaded = 95% CI. Reference = April 2025.

Figures 7a, 7b, and 7c present the full DiD event study comparing treated parcels to a clean control group (undamaged, >750m), controlling for building area, year built, tract pre-tornado vacancy rate, and ACS demographics. Pre-period DiD coefficients are uniformly insignificant. Post-tornado coefficients become increasingly negative, reaching approximately −1.0 log points by December 2025 under the $10,000 price filter (Figure 5a). Figures 5b ($5,000 filter) and 5c ($1,000 filter) show the same qualitative pattern with wider confidence intervals. The regression underlying Figure 5a yields $N = 966$, $R^2 = 0.743$.

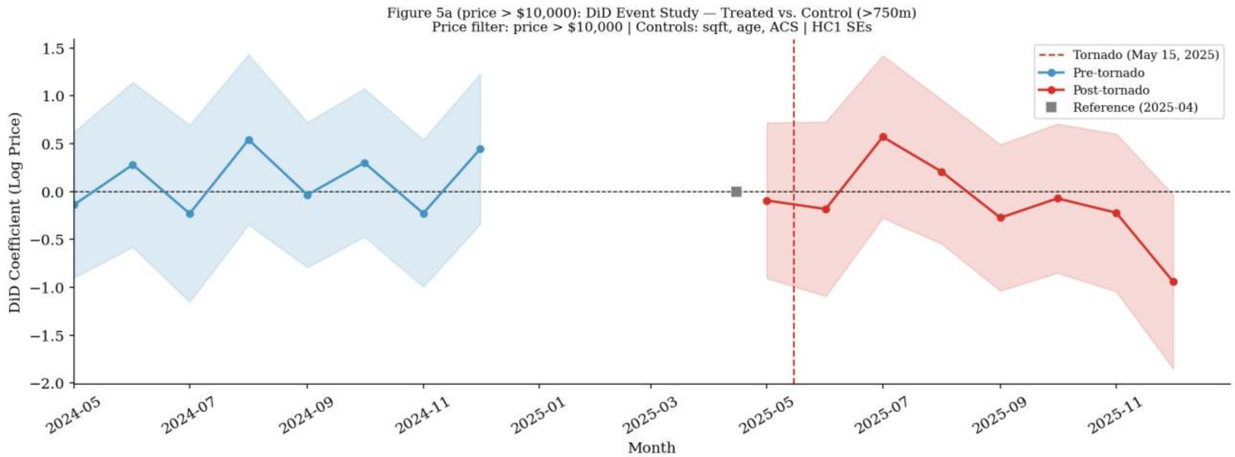

Figure 7a: DiD Event Study — Price > $10,000. Treated (≤250m) vs. Control (>750m). Controls: building area, year built, tract vacancy rate, ACS demographics, neighborhood FE. HC1 SEs. N = 966, $R^2 = 0.743$.

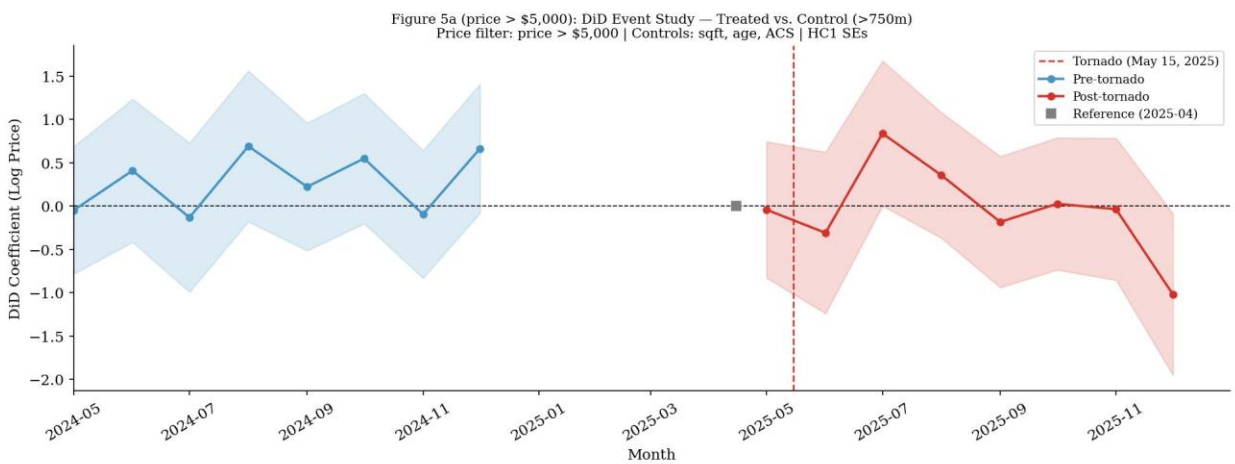

Figure 7b: DiD Event Study — Price > $5,000. Same specification as Figure 7a.

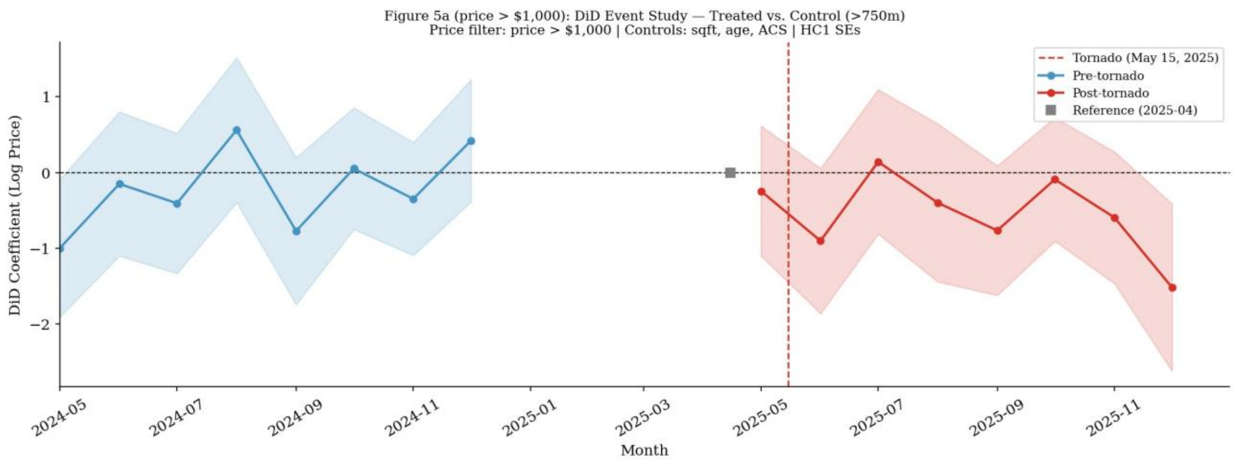

Figure 7c: DiD Event Study — Price > $1,000. Same specification as Figure 7a.

Table 6 below presents the full regression table underlying Figure 7a. The December 2025 interaction coefficient (−0.955, SE = 0.373, p = 0.011) is the only individually significant post-tornado term, consistent with effects deepening over time rather than an immediate single-period shock. All pre-period interactions are insignificant.

Table 6: DiD Event Study Regression — Treated (≤250m) vs. Control (>750m)

Variable	Coefficient	Std. Error	p-value	Sig.
NearDamage (main effect)	0.069	0.300	0.819	
× *2024-05*	−0.158	0.304	0.603	
× *2024-06*	0.386	0.367	0.292	
× *2024-07*	−0.331	0.396	0.404	
× *2024-08*	0.567	0.386	0.141	
× *2024-09*	0.250	0.319	0.434	
× *2024-10*	0.246	0.307	0.423	
× *2024-11*	−0.262	0.304	0.389	
× *2024-12*	0.285	0.323	0.379	
× *2025-05*	−0.120	0.334	0.720	
× *2025-06*	−0.198	0.440	0.653	
× *2025-07*	0.373	0.345	0.280	
× *2025-08*	−0.092	0.298	0.756	
× *2025-09*	−0.192	0.308	0.534	

× *2025-10*	−0.078	0.316	0.805	
× *2025-11*	0.028	0.362	0.939	
× *2025-12*	−0.955	0.373	0.011	**
Building area (sq ft)	0.000164	0.0000423	<0.001	***
Year built	0.00530	0.000668	<0.001	***
Tract pre-tornado vacancy rate	−5.041	3.953	0.202	
Median household income ($)	−0.0000101	0.00000493	0.040	**
% Black (tract)	−0.0497	0.00872	<0.001	***
Poverty rate (tract)	−0.00258	0.00512	0.615	
% Owner-occupied (tract)	0.00163	0.00415	0.695	
% Bachelor's degree+ (tract)	−0.0470	0.00975	<0.001	***

Observations: 966 R^2 = 0.743   Adj-R^2 = 0.713   Neighborhood FE: Yes   SE type: HC1 robust

*Note: Neighborhood FE coefficients suppressed (n = 70+). NearDamage is an indicator for whether each home sales observation was within 250 meters from the nearest damage point, while the control group was the sales observations at least 750 meters from the nearest damage point. *** p<0.01, ** p<0.05, * p<0.10.*

There are other aspects of the local housing market that can be analyzed in the context of this tornado. These include demographic effects, and variation across elementary school attendance zones with variation in vacant property locations. We first explore the demographic issues with a visualization. Figure 8 overlays the damage corridor on census tract median household income. The tornado path traversed predominantly low-income tracts (corridor medians ≈ \$20,000–\$50,000). Table 7 tests whether the spillover varies by income or racial composition. Triple interactions are near zero and far from significance (income: $\beta = 0.041$, $p = 0.856$; race: $\beta = 0.044$, $p = 0.839$), suggesting the home price spillover is uniform across the income and racial spectrum of affected neighborhoods.

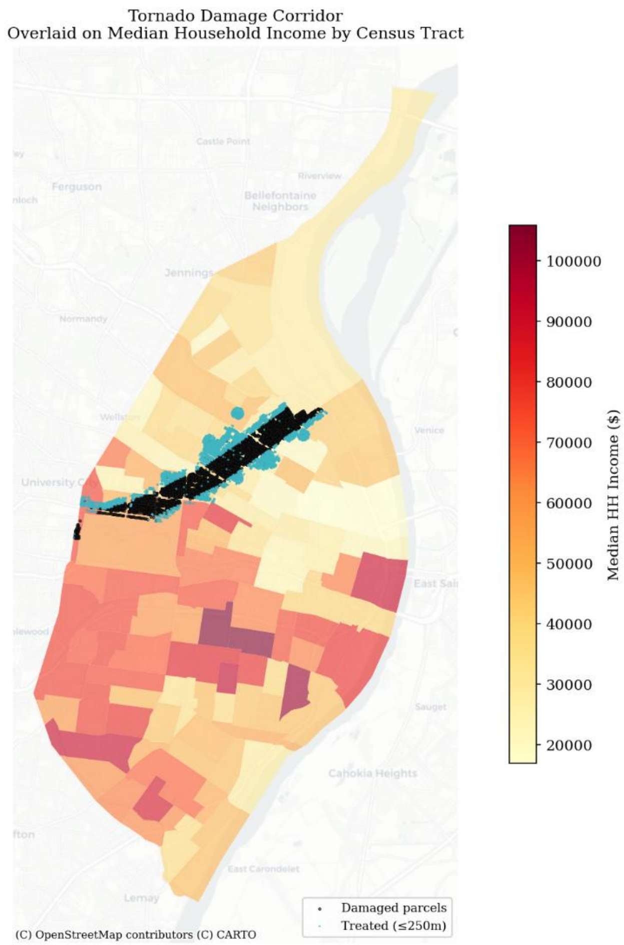

Figure 8: – Tornado Damage Corridor and Median Household Income by Tract

Table 7: Heterogeneity by Tract Income and Racial Composition

Interaction	Triple Interaction β	Std. Error	p-value
NearDamage × Post × High Income Tract	0.041	0.226	0.856
NearDamage × Post × Majority-Black Tract	0.044	0.219	0.839

Note: Separate OLS regressions. Property controls, ACS demographics, and neighborhood FE included. HC1 robust SEs. High income = above citywide median tract income. Majority-Black = % Black > 50.

Finally, we consider a school attendance zone analysis. Figure 9 shows there were several school attendance zones with an elementary school that closed (shaded red), in the damage path. In fact, the schools that closed were in heavily damaged areas, although other areas (shaded orange) had damaged homes but their schools did not close. It is noteworthy that the closed schools were in the relatively low-income areas, as can be seen by comparing Figure 9 with Figure 8, while the school attendance zones with heavy concentrations of damaged homes but without any school closures tended to be in areas with somewhat higher incomes. Also, Figure 10 demonstrates that the pattern of home vacancies is consistent with a cluster of vacant homes in the zones with schools that had closed. But there are other attendance zones with schools that did not close and had clusters of vacancies after the tornado.

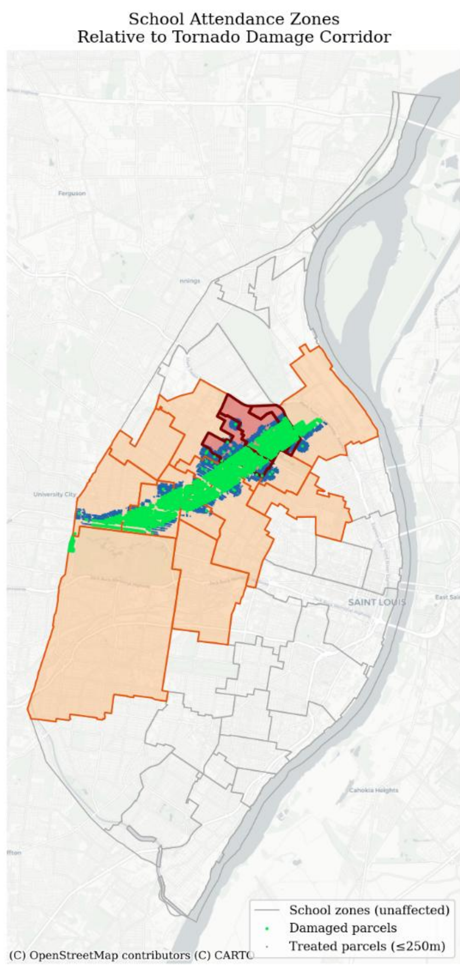

Figure 9 – School Attendance Zones Relative to Tornado Damage Corridor.

Note: Dissolved school zone boundaries. Closed zones (Ashland, Hickey) in dark red; affected open zones in orange; damage points in bright green.

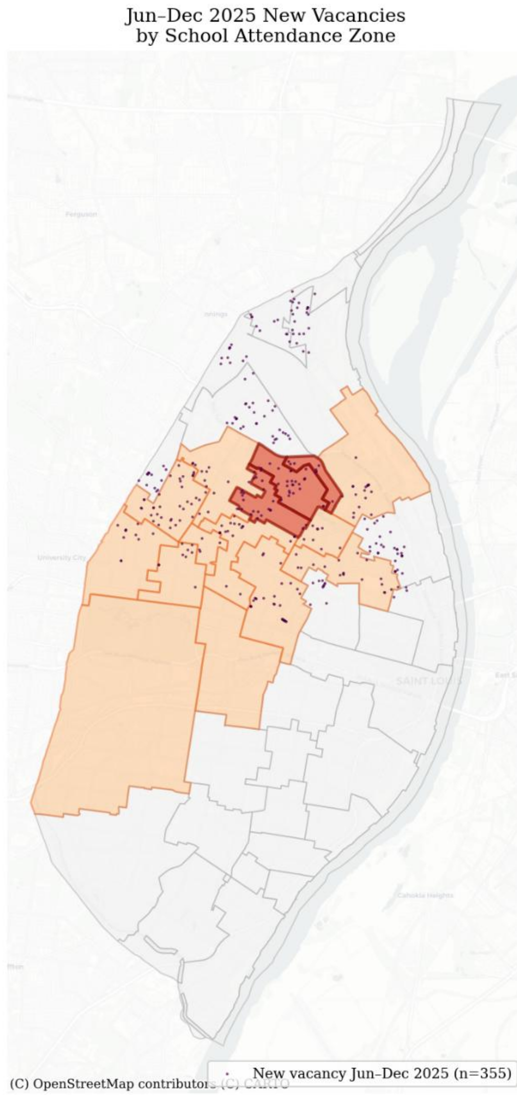

Figure 10 – School Attendance Zones and Newly Vacant Homes (dots), June to December 2025.

Note: New vacancy parcels by attendance zone. Affected and closed zones highlighted. No damage points shown.

To address potential balancing issues between treated (i.e., closed) and control (i.e., not closed) school attendance zones with damage points, we use a two-step procedure. First, because the full set of 17 control zones includes many with substantially higher pre-tornado median home prices than the two treated zones (Ashland: $43,000; Hickey: $43,000), we restrict the control group to the 5 nearest-neighbor zones by pre-tornado median sale price. The 5 retained control zones have pre-tornado median prices ranging from $38,000 to $43,900, closely bracketing the treated zone values. Second, within this restricted sample of 7 zones, we estimate zone-level propensity scores via logistic regression on demographic and housing market characteristics, and construct stabilized inverse probability weights (IPW).

Table 8 presents the balance table for the restricted IPW sample. Relative to the unrestricted sample, balance on pre-tornado median price improves substantially, as does the income balance.

Table 8 – Balance Table for Characteristics, IPW for School Attendance Zones

Variable	**Treat Mean**	**Control Mean**	**Std Diff (raw)**	**Std Diff (weighted)**
Median HH Income	$32,667	$34,200	−0.204	−0.271
Percent Black	95.6	94.9	0.278	0.181
Poverty Rate	25.2	35.7	−0.727	−0.646
% Owner Occ	43.1	43.3	−0.022	−0.114
Pre Median Price	$43,000	$40,580	0.719	0.393
Pre Vacancy Rate	0.070	0.096	−1.143	−0.898

Notes: Table 8 shows the balance of characteristics in the IPW sample of school attendance zones. The treated group are the zones with tornado damage points and elementary schools that closed, while the control group is the set of zones with damage points but no closed elementary schools. Based on the visual inspection of the sample mean of the treatment and control groups, the treatment and control samples appear to be reasonably balanced.

Table 9 presents the IPW-weighted DiD estimates for log sale price in closed versus open school zones. Parcels in closed school zones experienced price declines of approximately 20–22 log points (≈18–20 percent) relative to parcels in the matched open school zones. These estimates are consistent in direction and broadly similar in magnitude to the main proximity DiD results in Table 2, but are not statistically significant at conventional levels. The lack of statistical significance likely reflects the limited sample of treated zones (n = 2) and the residual covariate imbalance documented in Table 8, rather than the absence of an effect. We present these results as suggestive evidence that school closure may have compounded housing market disruption in affected zones, over and above the proximity-to-damage effect. However, we plan to further investigate this line of inquiry using alternative matching criteria.

Table 9 — IPW-Weighted DiD: Log Sale Price, Closed vs. Matched Open School Zones

	(A) No FE	(B) Nbhd FE	(C) Nbhd FE + ACS
Closed Zone × Post	−0.220	−0.213	−0.202
	(0.145)	(0.143)	(0.142)
Property controls	Yes	Yes	Yes
Neighborhood FE	No	Yes	Yes
ACS tract controls	No	No	Yes
Observations	1,431	1,431	1,430
R^2	0.474	0.675	0.693

Note: IPW-weighted WLS. Treatment = undamaged parcels in Ashland/Hickey attendance zones. Control = undamaged parcels in the 5 nearest-neighbor open school zones matched on pre-tornado median sale price. Property controls: building area, year built, assessed market value, bathroom count. HC1 heteroskedasticity-robust standard errors in parentheses. None of the Closed Zone × Post estimates are statistically significant at conventional levels (all $p > 0.10$).

7. Robustness Checks for Sales Prices

In some housing markets, sales prices may not reflect market transactions. In a city such as St. Louis, there are neighborhoods where many homes have very low values, and one might expect that a major tornado that makes a home uninhabitable could lead to perverse incentives for homeowners with property tax and/or mortgage balances. In other words, sometimes the sales prices can reflect the fact that a homeowner conveyed a home for a very low or zero sale price to pass along the property tax obligations to a new owner. Therefore, we see some potential insights could be gleaned from some robustness checks using alternative measures of home value opposed to the recorded transaction price.

In this robustness analysis, we estimate a series of hedonic regressions that follow the general difference-in-differences structure commonly used in the natural-disaster housing literature. Following Cohen and Gutowski (2026), the main analysis above focuses on whether sale prices differ systematically for homes located near the tornado path relative to those located farther away. As a robustness check, we repeat some of the above analyses, using “assessor transfer values” instead of the sales (or transaction) prices.

We begin by restricting the sample to arm’s-length transactions only, excluding all transfers where the recorded price likely does not reflect market value. Transfer value is used as the measure of sale price. Each regression controls for a rich set of housing characteristics, including age, square footage, and number of bathrooms, as well as an indicator for whether a property was vacant in 2024. Depending on the specification, we additionally include either census block group characteristics (median income and owner-occupancy rate) or census block fixed effects. All specifications include month-of-sale fixed effects.

Appendix Table A presents the estimates across a series of specifications that introduce distance-band indicators for proximity to the tornado path and their interactions with the post-tornado period. Across the 100-, 250-, and 500-meter bands, we observe evidence of price declines only for homes located very close to the damaged areas. Specifically, the interaction term for homes within 100 meters of the tornado path is negative and statistically significant in multiple specifications, with the implied sale-price discount ranging from roughly 60 to 75 log points after the tornado.

While the 250-meter and 500-meter bands also show negative coefficients on the post-tornado interaction, these results are smaller in magnitude and generally less precise, indicating that the effects attenuate quickly with distance.

The coefficients on house characteristics behave as expected in all specifications: larger and newer homes command higher prices, while older structures and those recorded as vacant in 2024 sell for significantly less. Block-level socioeconomic controls also retain the expected signs, with higher-income areas associated with higher prices and higher owner-occupancy rates linked to lower prices in some specifications. Together, these patterns support the internal consistency of the hedonic model.

Despite focusing exclusively on arm's-length transactions, we observe a non-trivial number of legitimate sales recorded at a transfer value of zero. Such cases, though limited, may reflect idiosyncratic recording practices or special-circumstance transfers. To address this concern and examine a valuation metric not subject to transaction-level noise, we re-estimate the same set of specifications using assessor-certified value.

Appendix Table B reports the corresponding results. Unlike the transfer-value regressions, the assessed-value models produce stark and statistically robust declines in valuation for homes located near the tornado-affected area. Interaction effects within the 100-, 250-, and 500-meter bands are large, negative, and significant across nearly all specifications, suggesting that assessors sharply downgraded the value of undamaged homes in the months following the tornado.

These estimated declines, however, appear unusually large relative to observed sale-price responses—an indication that assessor adjustments may have overshot true market effects.

Finally, to deepen our understanding of the underlying price dynamics, we are in the process of extending the analysis to a repeat-sales framework. This approach compares pre-tornado and post-tornado assessed values for the same homes, specifically those properties that transacted both before and after the tornado, even when the earlier sale occurred outside the 2024 window. This repeat-sales design offers an additional means of isolating tornado-related valuation changes from property-specific unobservables, and it will allow us to assess the persistence and magnitude of tornado effects with greater precision.

8. Conclusion

While the economic toll of natural disasters is typically quantified through the lens of direct physical destruction, this paper demonstrates that the true cost of extreme weather events extends beyond the immediate path of ruin. Exploiting the heterogeneous, highly localized damage corridor of the May 15, 2025, St. Louis tornado, this paper provides rigorous, parcel-level evidence of severe negative housing market spillovers on undamaged residential properties. By restricting our analysis to the relevant urban submarket north of the Lindell–Forsyth corridor and employing a difference-in-differences framework, we isolate the causal impact of disaster proximity on transaction prices, sales volume, and neighborhood vacancy dynamics.

Our findings reveal a dual-channel mechanism of neighborhood distress following the tornado. First, there is a rapid price capitalization channel that occurs in the areas closest to the damage points. Second, there is a slower, delayed displacement channel. Regarding the first channel, we find that undamaged properties located within 250 meters of the nearest point on the damage corridor experienced statistically significant price declines of 24 to 33 log points (approximately 21 to 28 percent), relative to control properties further away. These magnitudes are comparable to the findings of Cohen and Gutkowski (2026), who analyzed a tornado in the smaller city of Little Rock, Arkansas. Crucially, our distance gradient analysis shows that this capitalization is highly localized in St. Louis, with the steepest discounts heavily concentrated within the first 100 meters of the damage path and dissipating rapidly beyond the 250-meter mark. Robustness checks utilizing assessor transfer values and certified assessed values confirm these sharp valuation downgrades, suggesting that market participants and municipal assessors alike immediately internalized the severe negative externalities generated by the storm, such as debris, visual blight, and perceived future risk.

While price adjustments occurred rapidly, our analysis of probabilistic vacancy data uncovers a delayed displacement channel that is equally critical for understanding post-disaster neighborhood trajectories. During the immediate post-tornado months (June–August 2025), changes in vacancy rates near the damage corridor were statistically indistinguishable from broader seasonal trends. However, a highly significant spike in new vacancies emerged in the lagged window (September–December 2025) for properties within 250 meters of damage. This temporal disconnect between immediate price discounting and lagged vacancy onset suggests that while the housing market quickly prices in the disaster's disamenity value, the actual physical abandonment or withdrawal of housing inventory takes several months to materialize. This delay may reflect the time required for deferred maintenance to trigger inhabitability, for distressed landlords to halt leasing operations, or for the psychological toll of a degraded neighborhood environment to push marginal owner-occupants to leave.

Furthermore, this paper makes a novel contribution to the disaster literature by isolating the compounding effect of disaster-induced institutional shocks, specifically the abrupt closure of Ashland and Hickey Elementary Schools. Using an Inverse Probability Weighting (IPW) framework to achieve balance across closed and open school attendance zones, we demonstrate that the destruction of local institutional capital may amplify the physical damage externality, although more work is necessary to determine its significance. Because school quality and accessibility are heavily capitalized into residential real estate, the loss of these neighborhood anchors likely accelerated the downward pressure on housing values and upward pressure on vacancies. This highlights that natural disasters dismantle not only physical infrastructure but also the civic and institutional fabric that sustains urban neighborhoods.

From a distributional perspective, the St. Louis tornado traversed predominantly low-income and heavily minority census tracts. While our triple-interaction specifications indicate that the relative magnitude of the price spillover was uniform across the income and racial spectrum of the affected submarket, the absolute burden of these spillovers fell disproportionately on already vulnerable populations. In neighborhoods characterized by fragile housing markets and lower baseline home equities, a sudden 20 percent loss in property value for undamaged homes can severely impair household balance sheets and restrict future geographic mobility, effectively trapping residents in a declining environment. This general neighborhood blight might cause some residents to abandon their home or sell them for far lower prices, to flee these areas.

These findings carry implications for disaster recovery policy. Historically, private-sector, federal and municipal assistance, including insurance companies, FEMA grants, and city emergency aid, is targeted almost exclusively at properties suffering direct structural damage. Our results suggest that this narrow focus is insufficient for holistic neighborhood recovery. Because the uncompensated negative externalities of a disaster induce severe price depreciation and subsequent vacancy contagion in immediately adjacent undamaged homes, "buffer zone" stabilization funds might be one way to compensate nearby homeowners. Providing targeted financial assistance, property tax relief, or subsidized maintenance grants to undamaged homes within 250 meters of a disaster corridor could short-circuit the delayed displacement channel, preempting a cascade of urban blight before it takes root. Additionally, rapid municipal interventions to replace or reassign lost institutional anchors, such as schools, are vital to maintaining neighborhood viability.

We acknowledge several limitations that pave the way for future research. Due to the recency of the event, our observation window is limited to December 2025. With approximately 400 arms-length sales of undamaged homes in the post-tornado period, our estimates carry wide confidence intervals and capture only the short-run equilibrium. Cohen and Gutkowski (2026) find that the price effects from the Little Rock, Arkansas tornado disappeared by 9 months following the storm. It remains an open question whether these sharp price discounts and vacancy spikes in St. Louis represent a temporary overreaction or a permanent downward structural shift in neighborhood valuation. Furthermore, our reliance on property sales inherently excludes the rental market, which likely absorbed a significant portion of the displacement shock. Future research should extend this timeline to trace multi-year recovery trajectories, specifically employing a repeat-sales framework to control for unobserved parcel heterogeneity with greater precision. Investigating how pre-existing municipal policies, such as the distribution of code enforcement or the presence of community land trusts, might moderate these localized disaster spillovers will be essential for building resilient urban housing markets in an era of increasingly frequent severe weather events.

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9. Appendices

Appendix Table A – DiD Regressions, Transfer Value at Time of Sale as Dependent Variable

Transfer value regressions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11
		month D			month D			month D			montl
VARIABLES		block D	month D	month D	block D	month D	month D	block D	month D	month D	block
Post-Tornado	0.631	0.320	0.860	0.906	0.717	0.840	0.895	0.700	0.843	0.898	0.72
	(0.835)	(0.891)	(0.873)	(0.833)	(0.943)	(0.856)	(0.816)	(0.924)	(0.857)	(0.817)	(0.92
Within 100m			-0.0264	0.0439	-0.212						
			(0.159)	(0.157)	(0.182)						
W/ 100m Post-Tornado			-0.766**	-0.638*	-0.718*						
			(0.375)	(0.370)	(0.426)						
Within 250m						-0.0331	5.50e-05	-0.222			
						(0.152)	(0.149)	(0.176)			
W/ 250m Post-Tornado						-0.582*	-0.481	-0.499			
						(0.336)	(0.331)	(0.379)			
Within 500m									-0.00154	0.0701	-0.16
									(0.151)	(0.148)	(0.17
W/ 500m Post-Tornado									-0.601*	-0.512	-0.57
									(0.324)	(0.319)	(0.36
Sqft	0.000187***	0.000209***	0.000220***	0.000186***	0.000252***	0.000222***	0.000187***	0.000256***	0.000222***	0.000188***	0.00025
	(4.30e-05)	(4.38e-05)	(4.23e-05)	(4.28e-05)	(4.37e-05)	(4.23e-05)	(4.31e-05)	(4.35e-05)	(4.23e-05)	(4.29e-05)	(4.35e-
Baths	0.621***	0.725***	0.828***	0.627***	0.826***	0.826***	0.623***	0.825***	0.825***	0.624***	0.823*
	(0.171)	(0.149)	(0.169)	(0.170)	(0.174)	(0.169)	(0.170)	(0.174)	(0.170)	(0.171)	(0.17
Age	-0.00660***		-0.00798***	-0.00672***	-0.00825***	-0.00818***	-0.00685***	-0.00871***	-0.00818***	-0.00674***	-0.0086
	(0.00246)		(0.00250)	(0.00246)	(0.00282)	(0.00254)	(0.00249)	(0.00287)	(0.00256)	(0.00250)	(0.002
Vacant 2024	-0.574***		-0.845***	-0.589***		-0.840***	-0.583***		-0.829***	-0.575***	
	(0.213)		(0.216)	(0.212)		(0.217)	(0.213)		(0.217)	(0.213)	
Median Income	3.30e-05***			3.26e-05***			3.28e-05***			3.28e-05***	
	(4.76e-06)			(4.74e-06)			(4.75e-06)			(4.75e-06)	
% Owner Occ	-0.0142***			-0.0135***			-0.0137***			-0.0139***	
	(0.00478)			(0.00479)			(0.00481)			(0.00481)	

Constant	8.925***	7.715***	9.300***	8.645***	7.270***	9.336***	8.667***	9.321***	9.535***	8.810***	10.46*
	(1.077)	(1.311)	(1.047)	(1.080)	(1.443)	(1.032)	(1.069)	(1.475)	(1.000)	(1.044)	(1.36
Observations	2,125	2,224	2,126	2,125	2,126	2,126	2,125	2,126	2,126	2,125	2,12
R-squared	0.127	0.167	0.106	0.129	0.181	0.105	0.128	0.180	0.105	0.128	0.18

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

Appendix Table B – DiD Regressions, Assessor Value at Time of Sale as Dependent Variable

Assesor value regressions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
		month D			month D			month D			month D
VARIABLES		block D	month D	month D	block D	month D	month D	block D	month D	month D	block D
Post-Tornado	1.652*	1.422	1.938*	2.002**	2.111**	1.950**	2.027**	2.194**	1.991**	2.070**	2.260**
	(0.972)	(0.991)	(0.998)	(0.957)	(1.034)	(0.987)	(0.945)	(1.017)	(0.986)	(0.946)	(1.016)
Within 100m			-0.314**	-0.213	-0.330**						
			(0.137)	(0.136)	(0.159)						
W/ 100m Post-Tornado			-0.879**	-0.698*	-0.940**						
			(0.410)	(0.400)	(0.440)						
Within 250m						-0.252**	-0.203	-0.330**			
						(0.128)	(0.124)	(0.148)			
W/ 250m Post-Tornado						-0.745**	-0.600*	-0.832**			
						(0.362)	(0.353)	(0.387)			
Within 500m									-0.231*	-0.129	-0.205
									(0.126)	(0.123)	(0.145)
W/ 500m Post-Tornado									-0.843**	-0.718**	-1.005***
									(0.353)	(0.342)	(0.372)
Sqft	0.000341***	0.000370***	0.000383***	0.000335***	0.000420***	0.000388***	0.000337***	0.000424***	0.000385***	0.000337***	0.000425***
	(3.64e-05)	(3.75e-05)	(4.31e-05)	(3.64e-05)	(4.73e-05)	(4.12e-05)	(3.51e-05)	(4.35e-05)	(4.11e-05)	(3.53e-05)	(4.39e-05)
Baths	0.485***	0.673***	0.770***	0.488***	0.730***	0.769***	0.483***	0.729***	0.762***	0.482***	0.726***
	(0.125)	(0.120)	(0.136)	(0.124)	(0.136)	(0.137)	(0.123)	(0.136)	(0.136)	(0.123)	(0.136)
Age	-0.0103***		-0.0123***	-0.0106***	-0.0127***	-0.0129***	-0.0111***	-0.0134***	-0.0130***	-0.0111***	-0.0133***
	(0.00196)		(0.00204)	(0.00195)	(0.00227)	(0.00206)	(0.00195)	(0.00228)	(0.00207)	(0.00196)	(0.00229)
Vacant 2024	-0.599***		-0.978***	-0.621***		-0.974***	-0.613***		-0.952***	-0.599***	
	(0.210)		(0.206)	(0.210)		(0.204)	(0.209)		(0.205)	(0.209)	
Median Income	4.55e-05***			4.45e-05***			4.49e-05***			4.46e-05***	
	(4.24e-06)			(4.19e-06)			(4.22e-06)			(4.22e-06)	
% Owner Occ	-0.0222***			-0.0206***			-0.0211***			-0.0212***	
	(0.00432)			(0.00439)			(0.00440)			(0.00440)	
Constant	8.621***	8.123***	9.057***	8.264***	0.103	9.089***	8.284***	10.48***	9.426***	8.541***	10.39***

	(1.117)	(1.558)	(1.078)	(1.105)	(1.648)	(1.065)	(1.095)	(1.690)	(1.137)	(1.151)	(1.552)
Observations	2,125	2,224	2,126	2,125	2,126	2,126	2,125	2,126	2,126	2,125	2,126
R-squared	0.202	0.228	0.155	0.207	0.257	0.153	0.206	0.257	0.154	0.206	0.257

Robust standard errors in parentheses

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