Multifamily Housing: Property, Market Segment, and Owner **Characteristics' Influence on Hurricane Harvey Exposure and Impacts**

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(1) Research overview and key findings

Motivation: Multifamily rental housing (MFRH) is a significant, but understudied, portion of the housing stock (Peacock et al 2018). Findings related to disasters are dated, anecdotal, and not easily generalized. Limited available data for commercial real estate is a challenge. This research examines hazard risk, exposure, shorter-term disaster impacts, and longerterm recovery trajectories across MFRH differentiated by property, market segment, and owner characteristics.

Case study: Hurricane Harvey's (2017) impact in Harris County, Texas, was examined due to its extensive impacts, recency, and adequate time post-event to observe longer-term recovery outcomes.

Approach: We examine occupancy rates and property values for market-rate MFRH adjust to varied flood exposure intensity using proprietary property data linked to flood depth data. The sample consists of ~4,100 properties with ~598,000 housing units built before 2017. The indicators of property condition are examined (1) before disaster impacts, (2) immediately following disaster impacts, and (3) the period tracing out recovery through the 4th quarter of 2023. We explore dynamics across these periods. Event study models provide a broad picture of occupancy rate and property value dynamics across time. Then, using a series of regression models we examine how the characteristics of interest are associated with flood

Key findings highlight repeat flood impacts leading up to Harvey; properties with subsidized units were less atrisk pre-disaster; a post-disaster crowding toward and need for affordable housing; land use density coupled with building design can be effective mitigation tools; and certain owners locally headquartered with greater internal capacity had less short-term impacts.



Figure 1. Apartments flooded by Harvey in Houston, TX. hazard risk, actual flood exposure, and disaster impacts. arvey-12270464.php: https://s.wsi.net/public/resources/images/BN-UY070_3czKT_N

(2) Harvey's direct impacts were prolonged and devastating

- Initial landfall on August 25, 2017, near Port Aransas, TX with maximum sustained winds of 130 mph
- Harvey tracked back out to the coast, stalled over the Houston region and released 60 inches of rain
- Second landfall on August 30, 2017, in Southeast Texas and Western Louisiana
- 200,000+ homes and businesses were damaged, 30,000+ people displaced, and 89 people died Estimated damage of \$160 billion (inflation adjusted), 2nd most costly tropical storm behind Katrina (NOAA)



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(3) Linking property, owner, flood risk and exposure data

- Property coordinates with FEMA maps identify whether in or out of the 100-year flood zone.
- Average flood intensity per Census Block is determined using 30-meter resolution raster data and assigned to properties.



(4) Analysis of geographies can mask lower-level trends

 Despite extensive flooding, negative effects are
 Property-level analysis examines impacts more not observable for submarket geographies



(5) Occupancy rates and values fell for flooded properties

- Figures 5a and 5b plot event study model coefficients for the marginal difference in occupancy rates between properties that were flood exposed (treatment) and those that were not (control), controlling for property-specific characteristics and submarket-level trends (Miller, 2023).
- Results for occupancy rates (figure 5a) indicate no initial differences between treatment and control groups, an early decline from 2015 and 2016 flooding, a sharp decline into 3Q17 following Harvey, bottoming in 4Q17, and a return to market levels during 3Q19 (2 years post-Harvey)
- Results for property values (figure 5b) also indicate an early decline prior to Harvey, trough following Harvey in 2018, and recovery trend through 2020 consistent with the patterns observed for occupancy rates.



References

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- 3. Peacock, W. G., Dash, N., Zhang, Y., & Van Zandt, S. (2017). Post-disaster Sheltering, Temporary Housing and Permanent
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 Other property and owner characteristics, Census demographic data, quarterly occupancy rates, and assessed property values are also combined.

thoroughly, presented in the following sections.



Figure 5a. Effect of flooding on occupancy rates

(6) Flood risk tied to renovation, affordability, & ownership

Table 1 provides output for the flood risk and flood exposure models.

- The flood risk models examine how pro characteristics, market segments, and ov types and characteristics are associated a property being in the 100-year flood ze
- The flood exposure models examine ho the same set of characteristics are assoc with actual Harvey flooding.

Select highlights from the results:

- Significant flooding in and out of the 100 year flood zone \rightarrow some say flooding wa indiscriminate
- Recently renovated properties were mo likely to be in the 100-year flood zone an flooded \rightarrow indicates repeat flooding and flood-induced renovation
- Locally-based owners and owners with i properties in the Houston MSA more like own properties in the flood zone \rightarrow loca knowledge, willing to accept hazard risks
- Properties with subsidized units and tho that are user-owned were less likely to i flood zone; Properties with subsidized ur less flooded \rightarrow affordable housing development policy and practice

(7) Building height, rent level, & owner type moderated impacts

Disaster impact model output is provided in
 Table 2. Disaster impact models
 table 2 examining the changes between two log(val 2018) log(val 2018) Value (2018) Occupancy periods for occupancy rates and property -log(val 2015) agged dependent variable values. The general estimating equations are: flood intensity UNIT CONFIG (ref=studio) 2-Beds -0.1188 • $Y_2 - Y_1 = XB + \frac{flood + X\beta * flood}{flood + error}$ -0.1321PROPERTY SIZE (ref=[5,19] units Y₂ is a property's occupancy rate or property 0.0144 493.15 value after Harvey, Y₁ is before; -0.0215 -793.37 -0.0143 -485.24 Xβ is same set of variables as above; ROPERTY CHARACTERISTIC -0.0019 age in 2017 (years÷10) flood is the flood intensity measure, and 1=mid- or hi-rise 0.2200*** 0.0134 -371.79 -0.0149 =onsite property management 1=has affordable units 2.195.17* 0.0654+ RENT TIER (ref=lower) 0.0400+ lower-middle 950.06 variables in Xβ. 0.0173 -132.81 middle-upper 107.36 0.0111 Select highlights from the results: 721.37 0.0272 -0.0180 no rent data for property 848.43 VNER TYPE (ref=individual Columns (1), (3) and (5) indicate decline in -0.0102 nstitutiona 0.0557+ 0.3766** 3.455.98+ ublicly-traded occupancy rates, level and percent change i 0.0051 veloper/owner 1.272.97 -0.0124 other private values associated with increased flooding 0.0136 1,491.13 0.0768 0.0515 0.1726* 979.77 uncategorized. Mid- and hi-rise properties fared better than OWNER LOCATION (ref=MSA) -0.0187 -450.52 -0.0020 lower-rise (e.g., garden style, townhome) -1,373.84+ -0.0182 -1.351.82 Internationa 0.5751* 11,274.33 0.2485 uncategorized \rightarrow supportive of vertical development WNER SCALE Number of properties in portfolic Lower occupancy rates for higher-rent Number of properties in M Base effects and controls properties relative to lower-rent \rightarrow suggests Submarket fixed effects Number of observations 1.537 1.537 affordable housing demand/needs 0.0000 P-value 0.0000 0.0000 (Pseudo) R-squared 0.9134 0.1715 0.1900 Less short-term impacts for properties with Adjusted R-squared 0.9082 0.1367 0.1420 OLS Model type OLS subsidized units \rightarrow faster recovery, why? Robust standard errors Unit-weighted + *p* < 0.1, * *p* < 0.05, ** *p* < 0.01, *** *p* < 0.001 Notes: Observations are unit configurations nested within properties and are weighted by number of units for columns (1) and (2) and

- $Y_2 = Y_1 + XB + flood + X\beta^* flood + error$

- flood*Xβ is the interaction with select

- Publicly-traded owners (e.g., Camden) recovered more quickly because locally headquarted, internal capacity and scale, and likely, pre-established relationships

- 70NANB20H008. More information at http://resilience.colostate.edu/
- We thank Dr. Alexander Abuabara for help on some of the map figures.

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Table 1. Flood risk and exposure models

	(1) 1=in100yr	(2) flood	(3) flood intensity	(4) 1=in100yr	(5) flood	(6) flood intensi
		intensity	out of 100-yr		intensity	out of 100-y
CONSTANT	-2.1519***	0.4711*	0.5045*	-2.8432***	0.3341	0.4359
UNIT CONFIG (ref=studio)						
1-Bed				-0.1621	0.1480	0.1416
2-Beds				-0.1191	0.1765+	0.1782+
3-Beds				-0.1943	0.1801	0.2211+
HAZARD						
1=in 100 year		1.0114			1.1153***	
PROPERTY SIZE (ref=[5,19] units)						
[20,49]	0.7726*	0.2655*	0.3498*	0.9609**	0.2721*	0.3582
[50,149]	1.2621**	0.2302	0.2475	1.5073***	0.0945	0.1042
[150,299]	1.4246***	0.2228	0.2645+	1.8885***	0.0581	0.1150
[300,+]	1.2667**	0.1383	0.1344	1.7584***	-0.0328	-0.0244
PROPERTY CHARACTERISTICS						
age in 2017 (years÷10)	-0.1116*	0.0350	0.0352	0.0519	0.0167	0.0205
1=mid- or hi-rise	-0.1211	0.6615*	0.4966	-0.3828	0.2324	0.1033
1=has amenities	-0.1979	-0.2355*	-0.2831*	-0.1947	-0.2633**	-0.3176
1=renovated in past 2 years	0.5964***	0.4156**	0.3242*	0.6410***	0.4970***	0.3846
1=onsite property management	-0.2397	-0.0497	-0.0272	-0.3618*	-0.0988	-0.1200
1=has affordable units	-1.1116*	-0.1636	-0.2433*	-0.7581*	-0.2850**	-0.3991
RENT TIER (ref=lower)						
lower-middle	-0.3759+	0.0913	0.1187			
middle	-0.5756**	0.0475	0.0201	-0.6472***	0.0931	0.0149
middle-upper	-0.6525*	0.1551	0.0107			
upper	-0.8576**	0.0953	0.0225	-0.2406	0.4210***	0.2749
no rent data for property	0.1064	0.1539	0.1112	0.0694	0.1970	0.0675
OWNER TYPE (ref=individual)						
institutional	-0.3429	0.1395	0.1357	-0.2519	0.2457*	0.3106
publicly-traded	-0.7937	-0.2406	-0.2086	-0.6421	-0.0258	0.0054
developer/owner	-0.0328	0.0088	0.0395	-0.1707	0.1899*	0.2339
other private	-0.0146	-0.1808	-0.1626	-0.5327+	-0.0062	0.0111
user	0.0444	-0.1572	-0.0836	-1.3782**	-0.1234	-0.0862
.uncategorized	-0.1900	-0.0447	-0.0539	-0.2220	-0.0552	-0.1086
OWNER LOCATION (ref=MSA)						
Texas	-0.2495	0.0628	0.0168	-0.5906*	0.1407	0.0667
USA	-0.1469	0.1022	0.1134	-0.3415+	0.1646*	0.1528
International	0.4730	-0.0364	-0.1519	0.5941+	0.0411	-0.1435
.uncategorized	0.0538	-0.0659	-0.2382	0.7125	-0.2123*	-0.2044
OWNER SCALE						
Number of properties in portfolio	-0.0005	0.0006	0.0010	-0.0008	0.0002	0.0006
Number of properties in MSA	0.0186*	-0.0018	-0.0031	0.0135+	0.0004	-0.0015
Number of observations	2.235	2.235	1.973	4.960	4.960	4,336
P-value	0.0000	0.0000	0.0199	0.0000	0.0000	0.0000
(Pseudo) R-squared	0.0540	0.0615	0.0239	0.0609	0.0899	0.0000
Adjusted R-squared	0.0040	0.0013	0.0235	0.0005	0.08/5	0.0375
Model type	logit	019	015	logit	0.0045	0.0510
Robust standard errors	iogit /	/	/	10git	/	/
	v	v	v	v,	v	v
Unit-weighted				√	1	√

Notes: Observations are properties for columns (1) to (3) and unit configurations nested within properties for columns (4) to (6). Columns (4) to (6) are weighted by number of units. Robust standard errors. Untransformed coefficients reported for logit regression models. The owner type "institutional" includes owners such as banks, insurance companies, pension funds, and private equity; "user" includes owners such as housing agencies and non-profits.

properties also unit-weighted for columns (3) to (6). Columns (3) to (6) exclude properties with less than 20 units. Robust standard errors. Untransformed coefficients reported for fractional logit regression models. Lagged dependent variable for columns (1) and (2) are occupancy rates for 1Q15; for columns (3) and (4), 2015 property values. The dependent variable for columns (5) and (6) is the difference of the logged 2018 value and logged 2015 value. All values are standardized by the number of units in the property. Base effects are omitted from the table for brevity. All effects presented are the interaction between the variable and flood intensity measure.

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