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Catastrophe capitalization: Estimating the capitalization of extreme natural events across type and reoccurrence

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Abstract

Extreme natural events are associated with significant economic losses and expected to increase in frequency and intensity with time. While previous research has primarily investigated singular event types, the relative impact of multiple types of reoccurring events on the housing market has not been extensively studied. Filling this void in the literature, I estimate the housing price capitalization of numerous fire and flooding incidents in Southern California between 2000 and 2015. The results provide evidence that capitalization of extreme natural events is heterogeneous across type, time, and reoccurrence, and these variables are important when considering related policies involving outreach and education.

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1. Introduction

Extreme natural events threaten communities and are associated with significant economic costs, such as the destruction of natural environments, homes, businesses, and other property. In 2017, natural disasters resulted in $306 billion of total damage in the United States (NOAA 2018), and occurrences of these events are expected to escalate in frequency and intensity due to changing climate (National Academies of Sciences, Engineering, and Medicine 2016). Given the substantial costs associated with these incidents and their possibility to increase with time, it is important to understand household responses to extreme natural events and how these responses vary with event type and reoccurrence.

This research addresses the housing price capitalization of extreme natural events and advances the existing literature in two areas. First, I examine multiple types of extreme natural events in the same metropolitan area to determine the relative magnitude and persistence of their impact on housing prices, which has not been adequately studied in related research. Second, I add to the sparse literature investigating different locations and repeated occurrences of extreme events by determining if household responses change over time with these variables. To accomplish this, I estimate a hedonic model by regressing house prices against housing characteristics, neighborhood controls, and spatial-temporal fire and flooding data from Southern California between 2000 and 2015. The estimation results provide evidence that housing prices respond heterogeneously across event types. In particular, fires lead to larger decreases in housing prices than flooding within 18 months of the event after controlling for location, and the persistence of the price capitalization across time is dependent on the event type. The analysis is extended to show that capitalizations vary across event occurrences, where reoccurrences lead to larger price impacts than singular events. While this paper focuses on the Southern California area, the outcomes have implications for understanding resident risk perceptions and developing associated policies in other regions affected by similar incidents.

Previous studies have predominantly focused on estimating the impact of singular events, such as the degradation of home values from nearby wildfire (e.g. Loomis 2004) and flood hazards (e.g. Bin and Polasky 2004). Investigating the spatial effects of hurricane damage, Ortega and Taşpınar (2018) find that undamaged homes within the flood plain received a persistent price penalty following Hurricane Sandy, and that the price movements of damaged and undamaged homes converged with time. These results suggest that direct and indirect effects of extreme natural events exist and may be similar in the long-run. Bin and Landry (2013) address repeated occurrences of similar events, and find that the more recent hurricane was associated with a larger price differential for affected properties than the earlier occurrence. In similar research, Mueller et al. (2009) investigate repeated wildfires in Los Angeles County during the 1990s. Using the sample of affected homes with a regional housing price index, the authors determine that the second occurrence of a wildfire had a larger negative capitalization than the first occurrence, and attribute this result to changes in perceptions following the first event.[1]

[1] Building on their identification method in this research, I include all housing sales, not just those affected by extreme natural events during the study period, with spatial and temporal controls to eliminate the need for the application of a regional price index that could impact estimates if local price trends deviate from the larger region. In addition, I disaggregate event locations when estimating the capitalization of events.

Other connected research has focused on risk perceptions, and found that homebuyers do not accurately estimate location-based risk from extreme natural events (e.g. Chivers and Flores 2002; Champ et al. 2010). Kiel and Matheson (2018) show that risk perceptions change after a fire in nearby areas that were not directly affected, providing evidence that residents within the larger community are impacted by these events. Donovan et al. (2007) investigate the effectiveness of public outreach programs in Colorado seeking to educate local residents about fire risks. The authors initially estimate a positive relationship between housing prices and wildfire risk, but this relationship is eliminated after the implementation of the education program. Relatedly, Talberth et al. (2006) show that homeowners' willingness to pay for averting expenditures was positively influenced by the perceived efficacy of the expenditure, and the authors suggest that increased education can improve extreme natural event protection. I extend this literature by considering singular and repeated flooding and fire events throughout different locations in the same region to provide new insights on resident perceptions, as channeled through the housing market.

As the frequency, intensity, and reoccurrence of extreme natural incidents change, it is important to understand how residents respond to these events. In this paper, I estimate the effects of multiple extreme natural event types and occurrences on housing prices, and find that capitalizations occur in a varied manner. Housing prices are negatively impacted by flooding and fire events, and capitalizations depend on the time passed since the event and its reoccurrence. These estimates afford guidance for policymakers to implement outreach and education that recognizes reoccurrence probability and multiple event types, which may improve risk perceptions and related decisions.

2. Model

To empirically estimate the capitalization of multiple types and occurrences of extreme natural events, I apply the hedonic method (Rosen 1974). This method disaggregates housing prices into attributes of the house itself and the surrounding area. Therefore, the results provide evidence of resident values of the presence of (dis)amenities and responses to changes to these (dis)amenities. Following the logic from Tiebout (1956), residents maximize their utility based on their preferences when searching for, and bidding on, a home. The hedonic framework has been applied in a myriad of settings from valuing the closing of landfills (Kinnaman 2009) to determining the primary components of rental prices (Wang et al. 2012). Here, the price of a house is given as a function of its attributes (*H*), neighborhood attributes (*N*), and nearby extreme natural fire and flooding events (*E*), as shown below:

$$P_{it} = f(\boldsymbol{H_{it}}, \boldsymbol{N_{jt}}, \boldsymbol{E_t}) \qquad (1)$$

where *i, j,* and *t* index the house, neighborhood, and time, respectively. To estimate this relationship empirically, a log-linear function is used according to the discussion in Cropper et al. (1988) and Kuminoff et al. (2010).

$$\ln P_{it} = \alpha + \beta H_{it} + \gamma N_{jt} + \theta E_t + \eta_t + \nu_j + \epsilon_i \qquad (2)$$

In Equation (2), each coefficient signifies the percentage impact of a one-unit change in that variable on the price of a home, with correction for indicator variables (Halvorsen and Palmquist 1980). When estimating a hedonic model, spatial and temporal controls are necessary to eliminate unobserved variation that could bias the coefficients of interest. To address this issue, year fixed effects (η_t) are added to control for the time trend in prices for the sample, which has increases and decreases throughout the years studied. The variables (ν_j) represent spatial zip codes fixed effects for each property, and control for the differential in price due to proximity to the coast, public schools, and other unobserved spatially varying attributes. The extreme natural event variables (*E)* are included in the regression as indicator variables during the specified period between event occurrence and the housing sale. The neighborhood attributes (N_{jt}) include information on the flood and fire risk of an area to separate the impact of the extreme natural events from perceived risk or other unmeasured factors.

While Equation (2) identifies the capitalization of multiple extreme natural event types, the specification does not distinguish between the first or repeated occurrence of each extreme natural event type by location. To examine variance by time and location, Equation (2) is altered to include a subscript j for the extreme natural events. These additional variables allow for the estimation of each incident separately to determine the variance in capitalizations across incidents. Equation (3) presents this expanded equation used to examine event reoccurrence:

$$\ln P_{it} = \alpha + \beta H_{it} + \gamma N_{jt} + \theta E_{jt} + \eta_t + \nu_j + \epsilon_i \quad . \tag{3}$$

The estimated coefficients from Equation (3) indicate the effect of each occurrence for both flooding and fire. Therefore, these results provide evidence for the change in capitalization across event incidents.

Together, the models describe multiple facets of housing price responses to extreme natural events. First, Equation (2) determines the differential capitalization of fire and flood events. Then, Equation (3) demonstrates the extent that capitalization change across event locations and occurrences.

3. Data

Data from Orange County, CA between 2000 and 2015 are implemented in this study. This area is chosen because it is a highly populated area that has experienced multiple types of extreme events and may face increased risk due to a changing climate. The county is located between San Diego and Los Angeles counties, and has a population of over three million residents. While most of the area is developed and composed of relatively flat terrain, there are zones of dense brush and significant elevation changes in the far western and southeastern portions of the county. In these areas, wildfires and flooding leading to mudslides have occurred historically and are the primary extreme natural events that threaten residents.

Single family home sales data are obtained from Corelogic, a private data vendor. The sample includes all single-family homes that sold between 2000 and 2015 in the county. Data are cleaned to remove homes that sold multiple times in one year, homes that experienced abnormal appreciation, homes with missing information, and homes with other data anomalies. In total, there are 337,942 cleaned sales within the period. Summary statistics for the housing sales observations are provided in Table 1. In the sample of homes during the study period, the mean sales price is nearly $635,000, reflecting the relatively high cost of housing in this area compared to the national average. Areas impacted by fires have a similar sales price as the entire sample, while areas affected by floods have a mean price of nearly $1,220,000 due to the coastal area events. In addition, the mean home in the county has 2,000 square feet, with a lot size less than 0.16 of an acre.

Across the study period, CalFire, the state fire repository, is used to identify the fire events, and local news reports are used to identify the flood events. Fires in this area are the result of uncontrolled burning dry vegetation, while floods are associated with significant rainfall in a short period of time and are related with mudslides. Both events are connected to and strengthened by drought conditions. Five major flooding events and three major fires- Santiago, Freeway Complex, and Silverado- are identified in the county between 2000 and 2015. These events resulted in damage to multiple structures and were widely reported by local news outlets; therefore, the sample of extreme natural events is comprised of incidents likely to be widely observed and considered by homebuyers in the region. The flooding events are associated with direct water damage to structures and each was associated with debris or mudslide damage. The repeated occurrences of floods and fires were in the relatively remote mountainous communities in the eastern portion of the county, while the non-repeating occurrences in the sample took place throughout other eastern and western portions of the county. Figure 1 presents a map of the study area with Census tract outlines and identifiers for singular and multiple flood and fire locations. The lighter areas represent higher housing prices, which are typically toward the coastal and mountainous communities, and the darker areas represent lower housing prices.

The fire and flood event variables are matched spatially to each home within the neighborhood, or neighborhoods, which experienced damage or are accessed directly through adjacent areas with damage. These neighborhoods, measured at the Census tract level, are selected because they isolate the areas impacted by the events through direct property effects and indirect community-level effects, such as evacuations, road closures, and heavy emergency vehicle presence, while being large enough for sufficient observations.[2] Thus, the homes that are matched are those that were impacted by the event. The events are also matched temporally to housing sales within 18 months of the event occurrence, and varying this timeframe is investigated below. In Table 1, the extreme natural events are organized by location and occurrence, with independent locations for the fire and flood descriptors; that is, Location 1 is different for the flood and fire event variables. From the summary statistics, it was uncommon for homes in the county to be impacted by an extreme natural event. One-tenth of a percent of the housing sales were located in neighborhoods affected by a flood. In contrast, fire occurrences are observed for nearly four one-hundredths of the sample. These low numbers reflect that few homes were impacted and the majority of residents in the county are not directly threatened by these events.

4. Results

To estimate the capitalization of flooding and fire events, housing sales are spatially and temporally matched with extreme natural events. The extreme natural event variables (*E)* are

[2] If data allows, future research could consider the differential impacts of extreme natural events for residents within neighborhoods that contain flood, fire, or other relevant boundaries that would affect damage risk and resident perceptions.

given as indicator variables for the occurrence of the event within the specified period. Importantly, the estimates only reflect the capitalization of the extreme natural events on homes that are sold, and therefore existing, after the event. Homes that were destroyed or sustained major damage and were unable to be sold are not included in the sample after the event; thus, the costs associated with the loss of real estate are not reflected in this research. The area indicator variables, labelled flood area and fire area, are included in the regression to isolate the event capitalization estimates from event risk and other correlated attributes. These variables identify homes in areas experiencing flooding and fires during the study period, but outside the time period considered prior to the sale, and the extreme natural event coefficients are interpreted against these measures to identify their capitalization.

The estimates associated with the primary model investigating the capitalization of flooding and fire events are provided in Table 2. While spatial and temporal fixed effects are included in the regression, they are suppressed due to space concerns. Concentrating on the housing variables, the coefficients have the expected sign, significance, and magnitude, and are consistent with the existing literature. For example, homeowners prefer larger homes on lots with increased size, as signified by the positive and significant coefficient associated with these variables. Fireplaces, bathrooms, and pools are also positively capitalized by housing prices. Addressing event areas, the fire area coefficient is not statistically significant and provides evidence that these locations do not have substantially different prices when there is no event. In contrast, the flood area estimate is significant at the 1% level and represents a decrease in housing prices of nearly 15.4% for flood areas in the absence of an event. This measure reflects previous research finding a price discount in flood prone areas (e.g Bin and Polasky 2004) and suggests these areas may differ from others in unobserved ways, such as perceived event risk and lower elevation, which is related to views in the coastal and mountains areas that experienced flooding and would be capitalized by housing prices.[3]

Focusing on the variables in Table 2 that correspond with extreme natural events, each is negative and significant. The coefficient for flooding is significantly different from the flood area coefficient and represents a 1.9% decrease in the sales price of a home impacted by flooding when the location impact is removed. This corresponds to a nearly $12,000 price decrease at the county mean price level, and $23,000 at the mean price level for areas that experienced flooding. In comparison, the fire coefficient associated with a negative capitalization of 4.7%, or approximately $29,800 decrease at the county and fire affected area mean price levels. These estimates suggest that flooding and fire events are negatively capitalized by housing prices, with fire events having a larger impact within 18 months of the event.[4]

To determine the sensitivity of the estimated capitalizations to changes in the period considered, results from the main specification at varying lengths of time since the event occurrence are presented in Table 3. As expected, the housing coefficients are stable across the models.[5] Both the flood and fire coefficients are negative and significant across all periods, with

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[3] The area measures may be biased if past events have a persistent capitalization beyond the consideration period; however, these variables are the preferred method for controlling for flooding and fire areas given data availability and the period length is investigated in Table 3.

[4] A property fixed effects model (e.g. Palmquist 1982; Livy and Klaiber 2016) leads to similar qualitative results. However, the limited sample of repeated sales for properties affected by these events hinders identification.

[5] While the coefficients and corresponding standard errors presented in the table appear identical for many of the variables, the values vary beyond the rounding presented. In addition, a minor variance in these numbers is expected across models, given the small number of observations impacted by changing the time considered.

a general decreasing trend in magnitude as time progresses from 3 months to 24 months since the event. The flood event capitalization is more persistent in magnitude, while the fire effect dissipates more quickly and has varying significance between the 10% and 5% levels. These results show that housing price capitalizations of extreme natural events weaken heterogeneously as time passes since the occurrence.

Building on the results, Table 4 presents the model associated with decomposing extreme natural events by type, location, and occurrence to determine if the housing price capitalization changes across these variables. Compared to the previous specifications, the housing characteristic and event area estimates are similar. Focusing on the flooding variables, all are negative and significant. The low magnitude of the first occurrence coefficient at Location 1 may be explained by the fact that it is the first flood in the sample, and the first large flood in over five years in the county. On average, the first flood event across Location 2 and Location 3 is associated with a price decrease of nearly 2.3%, which is equivalent to $14,600 at the county mean price level and $28,000 at the flooded area mean price level. The estimate for the second occurrence of flooding at Location 1 during the sample period is associated with a negative capitalization of nearly 2.7%, and the third occurrence is associated with a negative capitalization of 13.5%. Together, the coefficients suggest an increasingly negative impact of flooding on housing prices as events reoccur in a single area. A possible weakness with the comparison across events is that the magnitude of damage from the floods was different between the occurrences. However, the resulting damage was similar for each of the events, and the first occurrence was associated with the loss of one life, while the future incidents were not associated with any deaths.

Investigating the fire coefficients in Table 4, the only significant estimate is for the second occurrence at a location. This reoccurrence is associated with a negative capitalization of approximately 11.6%. Notably, the reoccurrence had the smallest area of the three observed fires at nearly 1,000 acres and the preceding event at the same location covered approximately 28,000 acres. There is no statistically significant indication that non-reoccurring fires impacted housing prices during the 18 months following the event for each location, although the negative coefficients suggest that a larger sample may uncover a significant relationship. A few explanations are probable for this result: the fires in the sample typically lead to small amounts of property damage compared to flooding events; capitalization may occur and dissipate quickly, as evidenced by the time decay results; and residents are better educated about the fire risk than flood risk through news reports and public outreach. Collectively, the fire estimates show that homeowners may expect infrequent fires based on past trends, as evidenced by the insignificance of the coefficients associated with the first fire in each location. However, education may need to address the possibility for these events to reoccur more often with time given that the reoccurrence is associated with a negative and significant capitalization. Future research could consider additional events to determine the stability of resident perceptions across time and multiple reoccurrences.

5. Conclusion

Extreme natural events can result in substantial economic consequences, and this research addresses these by exploring the extent the housing market changes with the occurrence of fire and flooding events. This paper uniquely builds on the existing literature by investigating multiple extreme natural event types in a single spatial area, and adds to the scarce yet growing literature on spatially repeating events. The results show that extreme flooding and fire events are negatively capitalized into housing prices, with differences in magnitude and persistence with time. In addition, the negative impacts resulting from both types of events increase when there is a reoccurrence and provide evidence that resident perceptions are altered with reoccurrence. The estimates across all models suggest that responses to extreme natural events are not constant across type, time, and occurrence, and provide an initial step in determining how future possible changes in the frequency and intensity of extreme natural events will affect homeowner welfare.

These results have implications for policies surrounding extreme natural events. In the study area, wildfire education and media coverage are significant and the tempered housing price capitalizations for the fire areas and initial occurrence of fires may reflect local knowledge of the associated risks, mirroring the effect of education from previous research (e.g Chivers and Flores 2002). However, outreach may need to be altered to align risk perceptions with expectations of event reoccurrence in the face of a changing climate. The significant and increasing magnitude of capitalization for the flooding events with reoccurrence suggests that homebuyers may not be informed about the actual risks linked with these events. Further education in this area may lead to tempered capitalizations and a more efficient housing market, and officials should consider event type and frequency when developing and implementing extreme natural event policies.

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Appendix

Table 1: Summary statistics

Variables	mean	standard deviation
price	$635,644.20	$445,366.20
age	33.65	18.24
living square feet	2024.62	887.12
total baths	2.67	0.94
acres	0.16	0.15
fireplace	0.54	0.50
pool	0.24	0.43
flood	0.00114	0.03378
fire	0.00037	0.01923
flood 1, location 1	0.00017	0.01287
flood 2, location 1	0.00014	0.01179
flood 3, location 1	0.00013	0.01141
flood 1, location 2	0.00049	0.02222
flood 1, location 3	0.00021	0.01459
fire 1, location 1	0.00011	0.01032
fire 2, location 1	0.00013	0.01141
fire 1 , location 2	0.00013	0.01154
N	337942	

Table 2: Primary results

Variable	
Dependent Variable= ln(Price)	
age	-0.004***
	(0.001)
age2	0.000***
	(0.000)
sqft	0.030***
	(0.001)
bathroom	0.049***
	(0.014)
bathroom2	-0.008***
	(0.002)
acres	0.297***
	(0.042)
fireplace	0.017***
	(0.004)
pool	0.031***
	(0.004)
flood area	-0.168***
	(0.010)
fire area	-0.027
	(0.035)
flood	-0.187***
	(0.018)
fire	-0.048**
	(0.022)
constant	12.348***
	(0.026)
N	337942
R-sq	0.860

Note: Zip code clustered standard errors in parentheses. Zip code and year fixed effects estimates suppressed due to space concerns.

Significance given by * p<0.10, **p<0.05, and *** p<0.01

Table 3: Varying event timing

Variable	(1)	(2)	(3)	(4)	(5)
Dependent Variable= ln(Price)	3 months	6 months	12 months	18 months	24 months
age	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
age2	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
sqft	0.030***	0.030***	0.030***	0.030***	0.030***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
bathroom	0.049***	0.049***	0.049***	0.049***	0.049***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
bathroom2	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
acres	0.297***	0.297***	0.297***	0.297***	0.297***
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
fireplace	0.017***	0.017***	0.017***	0.017***	0.017***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
pool	0.031***	0.031***	0.031***	0.031***	0.031***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
flood area	-0.169***	-0.168***	-0.168***	-0.168***	-0.167***
	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)
fire area	-0.027	-0.027	-0.027	-0.027	-0.027
	(0.032)	(0.033)	(0.033)	(0.035)	(0.035)
flood	-0.225***	-0.219***	-0.201***	-0.187***	-0.190***
	(0.027)	(0.013)	(0.018)	(0.018)	(0.014)
fire	-0.125*	-0.103**	-0.046**	-0.048**	-0.043*
	(0.064)	(0.036)	(0.021)	(0.022)	(0.024)
constant	12.347***	12.347***	12.347***	12.348***	12.346***
	(0.025)	(0.025)	(0.025)	(0.026)	(0.026)
N	337942	337942	337942	337942	337942
R-sq	0.860	0.860	0.860	0.860	0.860

Note: Zipe code clustered standard errors in parentheses. Zip code and year fixed effects estimates suppressed due to space concerns.

Significance given by * p<0.10, **p<0.05, and *** p<0.01

Table 4: Individual event capitalization

Variable	
Dependent Variable= ln(Price)	
age	-0.004***
	(0.001)
age2	0.000***
	(0.000)
sqft	0.030***
	(0.001)
bathroom	0.049***
	(0.014)
bathroom2	-0.008***
	(0.002)
acres	0.298***
	(0.042)
fireplace	0.017***
	(0.004)
pool	0.031***
	(0.004)
flood area	-0.167***
	(0.011)
fire area	-0.029
	(0.034)
flood 1, location 1	-0.076**
	(0.035)
flood 2, location 1	-0.194***
	(0.036)
flood 3, location 1	-0.312***
	(0.023)
flood 1, location 2	-0.201***
	(0.011)
flood 1, location 3	-0.180***
	(0.012)
fire 1, location 1	-0.010
	(0.039)
fire 2, location 1	-0.123***
	(0.029)
fire 1, location 2	-0.007
	(0.035)
constant	12.342***
	(0.026)
N	337942
R-sq	0.860

Note: Zip code clustered standard errors in parentheses. Zip code and year fixed effects estimates suppressed due to space concerns.
Significance given by * $p<0.10$, ** $p<0.05$, and ***

Figure 1: Map of study area