The Price Effects of Natural Peril Risks

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Natural perils like hurricane wind, hurricane storm, inland flood, earthquake, and wildfire can have significant adverse economic impacts on the geographical areas that they affect. The National Oceanic and Atmospheric Association (NOAA) National Centers for Environmental Information (NCEI) reported that, after adjusting for inflation, there were 348 weather and climate disasters in the US that had overall damages in excess of $1 billion from 1980 to 2022 – total costs for all of these events exceeded $2.5 trillion. Florida accounted for 75, or more than 20%, of these billion-dollar events. From 1980 to 2022, the average annual number of U.S. weather/climate disasters was 8.1 events; the average was 18.0 events over the last five full calendar years (2018 to 2022). In 2022 alone, the US experienced 18 weather and climate disasters with costs that exceeded $1 billion. According to the Florida Office of Insurance Regulation, Florida experienced $14.4 billion in insured losses from Hurricanes Ian (September 2022) and Nicole (November 2022) as of March 2023. The increasing prevalence and intensity of climate-related disasters has garnered the attention of property owners, insurers, and governments.

With recent earthquakes showing a trend of increasing economic losses, real estate investors should also be attuned to earthquake risks. The U.S. Geological Survey (USGS) and the Federal Emergency Management Association (FEMA) indicated that the U.S. experienced 28 earthquakes with a magnitude of 6 or greater in the last ten years. In their recently published joint study, USGS and FEMA estimated the annualized earthquake loss in the U.S. The study found that earthquakes cost the U.S. an estimated $14.7 billion annually in building damage and associated costs; this amount doubled the last estimate that was determined in 2017. Although earthquakes are a national problem, California has accounted for nearly two-thirds of the economic losses; Los Angeles has accounted for nearly a quarter of the total.

This study explores the price effects of natural peril risks. Specifically, using property-specific risk peril scores and transaction data from CoreLogic and Urban Institute census tract data, it examines the impact of natural hazard risks on apartment sales prices in the Miami and Los Angeles metropolitan areas from 2005 to 2022. Given investors' increasing awareness of hazard risks, higher natural peril risks are expected to have placed downward pressure on property prices through time.

Existing literature on whether property buyers and investors have accordingly priced natural perils into the prices they paid remains rather mixed. One important challenge in empirically capturing the capitalization of a peril is the ability to isolate such impact

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among the many pricing factors. If there is material capitalization of hazard risks, one can expect such impact to show up more frequently on the valuations of properties with a large risk exposure and potential losses relative to those with a low or modest risk exposure. Built on this intuition, the analysis was designed to allow for potentially differential impacts on high-risk and low-risk exposure apartment properties. In addition, this research built upon existing studies which have pointed to a significant shift and development in the public sentiment towards climate risk. Empirically, this rising public/investor awareness of climate risk provides a natural experimental setting to evaluate potential impact of natural peril risks on property valuations.

CoreLogic Risk Methodology

CoreLogic is a leading industry provider of catastrophe models. The models are used widely by insurers, reinsurers, government agencies, banks, and other organizations. CoreLogic's Risk Quantification & Engineering® (RQE) catastrophe risk modeling software platform allows users to quantify and manage the potential financial impact of natural hazards including hurricane wind, hurricane storm surge, inland flood, earthquake, and wildfire. For real estate, the platform is typically used to assess the risk of property damage related to a given peril. The model estimates the full probabilistic distribution of damage and loss under simulated scenarios of catastrophe frequency, severity, and location. RQE calculates average annual damage and loss estimates, as well as annual probability exceedances, e.g., 100-year losses, using a database of event simulation results to develop average annual loss rates for each property site. Scenario and average annual damage and losses can also be calculated for individual property sites, geographic aggregates, and portfolios of residential and commercial properties.

Natural disasters have become costlier in recent years; much of this increase has been related to increases in exposure, labor and supply costs, and economic inflation. The effects of climate change related to cumulative carbon emissions has also become noticeable. Many scientists project that the North Atlantic Basin will have more category 4 and 5 hurricanes because of climate change due to projections of future greenhouse gas emissions and energy consumption. The Intergovernmental Panel on Climate Change (IPCC) includes representative concentration pathway (RCP) scenarios that project future carbon emission scenarios. RCP8.5, known as the business-as-usual scenario, projects that carbon emissions will continue to increase exponentially through the remainder of the century without any reductions related to green technologies, emission reduction regulations, and/or fossil fuel resource depletion. A different climate scenario is represented by the RCP4.5, which projects that humanity will eventually begin to reduce carbon emissions in the middle of this century, and that these reductions will be related to any combination of implementing renewable energy sources and other green technologies, carbon emissions regulations, or other causes. CoreLogic's RQE includes models that account for the effects of climate change using several climate change projections and time horizons. The RCP8.5 and RCP4.5 projections account for changes in the frequency of events and sea level rise at 2050. In contrast to the RCP8.5 and RCP4.5, a baseline scenario of climate models accounts for climatology for the last 120 years, i.e., 1900 to the present, without any adjustments to climate change.

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Exhibit 1
CoreLogic's Hazard Map for Miami

Exhibit 1 displays Miami's hazard risk under the baseline, RCP4.5 – 2050, and RCP8.5 – 2050 scenarios. Low, middle, and high levels of risk are indicated by green, yellow, and red shading, respectively. Moving across the scenarios (from baseline to RCP4.5 to RCP8.5), increasing risk is highlighted by the greater and darker red shading. Risk projections are expected to be higher in 2050 due to climate change, stemming from a combination of sea level rise and higher frequency of major hurricanes. Locales with the highest risk occur in areas near the coast and in the wetlands of the Everglades west of Miami. Non-coastal urban areas have the lowest risk due to longer distances from the storm surge waters and the reduction of hurricane winds due to friction from land. Miami's risk is primarily driven by hurricanes; inland flood from non-tropical cyclones and wildfires are also contributors. Much of the area's exposure is within 20 kilometers of the ocean and is subject to a high degree of risk.

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Exhibit 2
CoreLogic's Hazard Map for Los Angeles

Exhibit 2 presents Los Angeles' hazard risk under the baseline, RCP4.5 – 2050, and RCP8.5 – 2050 scenarios. Low, middle, and high levels of risk are indicated by green, yellow, and red shading, respectively. Risk increases when moving down the scenarios (from baseline to RCP4.5 to RCP 8.5). Areas with the highest risk, or darkest red shading, generally occur inland; these areas also tend to have higher elevations. Many coastal areas have the lowest risk. Los Angeles' risk is primarily driven by earthquakes, but inland floods and wildfires also contribute. Note that earthquake ground-shaking is not impacted by climate change, however, earthquake fire-following risk is projected to rise due to climate change which is expected to create more favorable conditions for fires.

Apartment Transaction Activity

The CoreLogic public record database was accessed to obtain multifamily transactions data for Miami and Los Angeles from January 2005 to December 2022. Only arms-length property transactions were included in the analysis. The data was further filtered, excluding observations with missing property characteristics and outliers within each of the variables. Miami initially had 17,049 multifamily transactions over the 2005 to 2022 time period. All transactions in Palm Beach County were excluded from the analysis as the county does not record an apartment's total number of units in its public record data. The final Miami sample consisted of 7,792 transactions. Los Angeles initially had 60,415 apartment transactions. Similar to Palm Beach County, all transactions in Orange

County were omitted from the analytics due to missing data. The final Los Angeles sample included 36,187 transactions; all were located in Los Angeles County.

The hazard risks for Miami and Los Angeles are primarily driven by hurricanes and earthquakes, respectively. Using the binary variable HiRiskH and a threshold of 1% average annual damage ratios, the Miami apartment transaction data was split into two risk-based groups: areas subject to high average annual damage ratios from hurricane winds and storm surge (HiRiskH=1) and those that were not (HiRiskH=0). For Los Angeles, risk focused on the average annual damage ratios from earthquakes. Using a 0.25% damage ratio threshold, the binary variable HiRiskEQ equaled one for the high-risk group and zero otherwise.

The construction of risk-based sampling was used in order to better isolate and capture the potential risk-specific pricing component. In addition, the analysis adopted a testable assumption that the 2013/2014 time period constituted a valid shift in the perception and awareness of climate risk (Keys and Mulder, 2020). As a result, the examined timeframe, 2005 to 2022, was split into two equal intervals: 2005 to 2013 and 2014 to 2022. If property investors have become more aware of natural hazard risks in the post-2014 time period, greater incremental price discounts would be anticipated in the post-2014 period compared to the prior time frame. Exhibit 3 lists annual apartment transaction dollar volumes and property counts for Miami and Los Angeles by hazard risks from 2005 to 2022.

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Exhibit 3
Apartment Transaction Activity for Miami and Los Angeles by Hazard Risks

Property counts highlight the historical ebb and flow of transaction activity across Miami and Los Angeles. It may bear a reminder that reported transactions do not capture all transactions that occurred during the time period but include only those that were used in the model estimations. Intuitively, property count tallies generally slowed during the Great Financial Crisis (roughly from 2007 to 2011) and the onset of the COVID-19 pandemic (2020). For Miami, the high hurricane risk areas had an extended slowdown starting in 2017. The count drop-offs experienced in 2022 were likely due to the rising interest rate environment. Reflecting the significant run-up in property prices since the Great Financial Crisis, post-2014 transaction dollar volumes were significantly larger than their respective pre-2014 counterparts. A review of the table indicates healthy transaction activity across all risk categories in both Miami and Los Angeles.

Repeat Sales Apartment Price Indices

Utilizing a weighted least squares repeat sales methodology, CoreLogic transaction data was used to construct apartment price indices (APIs) for Miami and Los Angeles. In constructing the repeat sales-based price indices, only arms-length multifamily transactions that occurred between January 2000 and December 2022 were utilized; they were appended with their prior sales, if available. A minimum holding period of 12 months between the two sales dates was required to be considered a sales pair. In addition, sales pairs with an annual rate of price appreciation in the top or bottom one percentile were filtered out to exclude potential outliers. Partitions of the repeat sales sample for constructing risk-based price indices followed the same risk classifications used throughout the analyses.

Exhibit 4 shows the Miami repeat sales four-quarter moving average smoothed APIs for high (HiRiskH=1) and non-high (HiRiskH=0) hurricane risk areas from 2005 to 2022. Exhibit 5 indicates average rolling four-quarter price changes from the Miami risk-based APIs in the pre-2014 (2005 to 2013) and post-2014 (2014 to 2022) time periods.

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Exhibit 4
Miami Repeat Sales Smoothed Apartment Price Indices by Hurricane Risk

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Exhibit 5
Average Rolling 4-Quarter Price Changes from Miami Smoothed APIs

Exhibit 4 shows that the Miami smoothed APIs followed similar paths, but the HiRiskH=1 series exhibited a jaggedness, while the HiRiskH=0 series displayed a smoothness over the sample period. The greater volatility of the high hurricane risk category likely stems from the smaller number of paired sales in its repeat sales index. Exhibit 5 shows that average rolling four-quarter price changes for the Miami HiRiskH=1 and HiRiskH=0 groupings in the pre-2014 timeframe were 0.09% and -0.33%, respectively. The high-risk category posted an average four-quarter price gain of 11.31% in the post-2014 period; the non-high-risk average gain was 11.58%. The average rolling four-quarter price changes for the higher and lower hurricane risk groups were very similar in the pre- and post-2014 periods, and it showed no statistical differences.

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Exhibit 6
Los Angeles Repeat Sales Smoothed Apartment Price Indices by Earthquake Risk

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Exhibit 7
Average Rolling 4-Quarter Price Changes from the Los Angeles Smoothed APIs

Exhibit 6 shows that the Los Angeles smoothed APIs fairly closely tracked one another through 2014, but afterwards an increasing divergence was evident. The California Earthquake Authority (CEA) reported an increase in earthquake insurance policy sales after the 5.1 La Habra earthquake near Los Angeles in March of 2014 (Ousley, 2014); a 6.0 earthquake was also reported in Napa in northern California in 2014. These events suggest that earthquake risk awareness in Los Angeles may have become more prevalent after 2014 and it may have placed downward pressure on apartment prices from that time. Exhibit 7 indicates that the average rolling four-quarter price changes for both groups were similar over 2005 to 2013 with the HiRiskEQ=1 gain (4.10%) slightly higher than that of the HiRiskEQ=0 group (3.83%). Post-2014, the high earthquake risk category posted an average four-quarter price gain of 7.82%; the non-high-risk average gain was 8.53%. Statistically, the two risk groups showed no significant difference in the rate of price appreciation.

Data and Descriptive Statistics

Data from CoreLogic, a leading global property information, analytics, and data-enabled solutions provider, were used to explore the impact of natural hazard risks on apartment prices in Miami and Los Angeles. In addition to a property's zip code and census tract location, qualified opportunity zone (o-zone) tract information from Urban Institute, a non-profit economic and social policy research organization based in Washington, D.C., was utilized to map each property to designated o-zones. The overall data set included the following variables:

PropSP	is the property sales price;
PropNumUnit	is the number of units in the apartment building;
PropLand	is the property's land area in acres;
PropAge	is the apartment's age in years;
PropBltRatio	is the ratio of the apartment's number of units to its land area;
OZone	is a binary variable that equals one if the property is located in a qualified opportunity zone;
HurricaneWind	is the average annual damage ratio between the repair and total replacement cost of the building caused by hurricane winds; and
EarthQuake	is the average annual damage ratio between the repair and total replacement cost of the building caused by earthquake ground-shaking and fire-following.

Qualified opportunity zones were established by the Tax Cuts and Jobs Act of 2017. They are a place-based community development program that encourages the investment of private capital investment into economically challenged urban and rural areas throughout the United States and its territories through the use of tax incentives. If certain conditions are met, investors can defer, reduce, and avoid capital gains taxes on the timely investment of their capital gains into qualified opportunity funds that invest in businesses and properties located in o-zones. The program's constructs have created conditions that are ripe for rising real estate prices. The existing literature has found o-zone price premiums for development and redevelopment properties (Sage, Langen, and van de Minne, 2019), apartments (Pierzak, 2021), and single-family homes (Mayer and Pierzak, 2021).

Exhibit 8 lists apartment transaction variables for Miami and Los Angeles and provides descriptive statistics for their respective risk-based groups (HiRiskH and HiRiskEQ).

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Exhibit 8
Descriptive Statistics

Apartment transactions located in high hazard risk areas in Miami and Los Angeles accounted for approximately 27% and 17% of total transactions, respectively. Comparing the risk-based groups within each metropolitan area, some notable differences were evident in the property and location variables. While the overall average apartment sales prices were similar in Miami, the HiRiskH=1 multifamily properties tended to be smaller, older, more dense properties that were more expensive on a per unit basis than their lower risk counterparts; less than 2% of these apartments were located in o-zones. In Los Angeles, the overall average apartment sales prices were also similar, but the apartment properties located in high earthquake risk areas tended to be larger, newer, less dense properties that were less expensive on a per unit basis compared to the lower risk group; over 25% of these multifamily properties were located in o-zones.

The HurricaneWind average annual damage ratios for Miami's high hazard risk group exceeded one percent in some locations and this can be interpreted as the structures expecting total damage more than once per century. While the HurricaneWind averages differed considerably between Miami's risk-based groups, Los Angeles' EarthQuake averages offered less distinction. The EarthQuake average annual damage ratios for Los Angeles' high and lower hazard risk groups were 0.27% and 0.20%, respectively. The modest spread raises a concern that the high hazard risk group may not be differentiated enough from its counterpart; this may have implications for the regression analysis. With the HiRiskEQ=1 group only accounting for 17% of Los Angeles' apartment transactions, it would be difficult to refine the measure further.

Empirical Methodology and Results

Hedonic pricing methods were used to analyze the data. Using a difference-in-differences (DiD) design, price dynamics in the Miami and Los Angeles apartment markets were examined. The empirical models (1) allow high and low risk exposure properties to appreciate at different rates due to their risk exposure to the natural peril, and (2) leverage DiD estimators to capture potential impact of a rising awareness of natural peril risk on apartment values or potential apartment sales price discounts associated with high natural peril risks. The dependent variable in the DiD estimation was the natural log of property sales price, lnPropSP. The independent variables included:

lnPropSP	is the natural log of property sales price;
lnPropNumUnit	is the natural log of the number of units in the apartment building;
lnPropLand	is the natural log of the property's land area in acres;
lnPropAge	is the natural log of the apartment's age in

	years;
PropBltRatio	is the ratio of the apartment's number of units to its land area;
OZone	is a binary variable that equals one if the property is located in a qualified opportunity zone;
HurricaneWind	is the average annual damage ratio between the repair and total replacement cost of the building caused by hurricane winds;
HighRiskH	is a binary variable that equals one for areas subject to high average annual damage ratios from hurricane winds and storm surge;
EarthQuake	is the average annual damage ratio between the repair and total replacement cost of the building caused by earthquake ground-shaking and fire-following;
HighRiskEQ	is a binary variable that equals one for areas subject to high average annual damage ratios from earthquakes;
D20##	is a set of binary time variables that equal one if the apartment sold in a particular year with years ranging from 2005 to 2022;
HighRiskHxD20##	is an interaction variable that multiplies HighRiskH and D20##;
HighRiskEQxD20##	is an interaction variable that multiplies HighRiskEQ and D20##;
DPeriod####-####	is a set of binary time variables that equal one if the apartment sold in a particular time period with periods ranging from 2005 to 2007, 2008 to 2012, 2013 to 2015, 2016 to 2019, and 2020 to 2022, respectively;
HighRiskHxDPeriod####-####	is an interaction variable that multiplies HighRiskH and DPeriod####-####; and
HighRiskEQxDPeriod####-####	is an interaction variable that multiplies HighRiskEQ and DPeriod####-####.

The baseline scenario from CoreLogic's RQE was utilized in all DiD estimations. An effort was made to incorporate the RCP4.5 and RCP8.5 projections into the models on *a priori* assumption that projected climate change may separately impact property valuation. However, a nearly perfect correlation was found between these projections and the baseline based on either the correlation in damage ratios or the rank correlation. The RCP4.5 and RCP8.5 projections, as well as their projected differences from the baseline scenario, were not included in the models. Exhibit 9 displays the DiD estimation results for the first of two Miami models; Model 1 employed calendar years for the binary time variables.

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Exhibit 9
Miami: Model 1 Difference-in-Difference Estimations

In the first Miami model, DiD coefficients were estimated using 18 individual year dummy variables. These calendar year variables allowed for a more continuous measure and tracing of the dynamics of DiD coefficients before and after a shift in the heightened awareness of climate risk and its resulting impact. A potential drawback of using 18 individual calendar year dummies is on the accuracy and reliability of estimated DiD coefficients when individual-year observations on HighRiskH=1 become quite thin.

Treating 2014 (the assumed year when heightened awareness of climate risk commenced) as the base year, HiRiskHxD2014 was omitted from the equation, thus, providing a point of comparison. All the interaction variable coefficients were negative; 12 of 17 coefficients were significantly different from zero at the 90%, 95%, or 99% levels of confidence. These results indicate that Miami's apartment investors have had a longstanding awareness of hurricane risk and priced this natural peril risk into their multifamily acquisitions. Percentage differences calculated from the coefficients capture the incremental apartment price changes for Miami properties located in high hurricane risk areas.

The R^2, or explanatory power, of the regression was 54.4%. All the coefficients for the non-time independent variables with the exception of lnPropLand were significantly different from zero at the 99% level of confidence. Of these property-specific variables, lnPropNumUnit was the explanatory variable with the largest impact on sales price. Its coefficient is the price elasticity with respect to an apartment's number of units. For a 10% increase in an apartment's number of units, sales price is expected to increase by 8.9%. The coefficient for lnPropAge is also a price elasticity. Holding all else equal, sales price is expected to decrease by 1.7% with a 10% increase in a property's age. OZone exhibited a negative relationship with lnPropSP; an intuitive outcome given that economically challenged and capital starved areas tend to be associated with lower property prices.

Interestingly, HurricaneWind and HiRiskH displayed positive relationships, likely attributable to the greater desirability of their locations. Together they suggest a nonlinear relationship between prices and risk exposure. The time dummy variables, D2005 to D2022, appear to have adequately captured the historical apartment price trends; D2014 was omitted for comparison purposes.

Exhibit 10 displays the DiD estimation results for the second Miami model. Recognizing that the numbers of observations in some years are quite thin which affects the accuracy and reliability of the estimated DiD coefficients, Model 2 utilized time periods that included a range of years rather than individual calendar years for the binary time variables.

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Exhibit 10
Miami: Model 2 Difference-in-Difference Estimations

The results for the second Miami model were very similar to those of the first model. All the coefficients for the non-time independent variables had the same signs and levels of statistical significance; they also had similar magnitudes. The time period binary variables also appear to have captured Miami's historical apartment price dynamics. For the interaction variables, again, all the coefficients were negative. The coefficients for HiRiskHxDPeriod2008-2012 and HiRiskHxDPeriod2020-2022 were significantly different from zero at the 99% level of confidence; the coefficient for HiRiskHxDPeriod2005-2007 was significantly different from zero at the 90% level of confidence. Holding all else equal, sales price is expected to be 21.0% lower for an apartment in a high hurricane risk area sold in the 2008 to 2012 time period compared to the 2013 to 2015 time period; the relative discount was 19.5% in the 2020 to 2022 time period. These results provide evidence of a consistent discount for apartments in high hurricane risk zones relative to their lower risk counterparts. A test of statistical difference between pre-2014 and post-2014 DiD coefficients indicated that the relative price discount has not changed in the post-2014 time period.

Exhibit 11 displays the DiD estimation results for the first of two Los Angeles models; Model 1 employed calendar years for the binary time variables.

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Exhibit 11
Los Angeles: Model 1 Difference-in-Difference Estimations

In many ways, the results for the first Miami and Los Angeles models were similar. For the Los Angeles model, the R^2 was 54.8%. All the coefficients for the non-time independent variables with the exception of lnPropLand were significantly different from zero at the 99% level of confidence. Of these property-specific variables, lnPropNumUnit was the explanatory variable with the largest impact on sales price. For a 10% increase in an apartment's number of units, sales price is expected to increase by 8.3%. Holding all else equal, sales price is expected to decrease by 2.8% with a 10% increase in a property's age. OZone exhibited a negative relationship with lnPropSP. The time dummy variables also appear to have adequately captured the historical apartment price trends.

In contrast to the first Miami model, the estimated coefficients on the Los Angeles hazard risk variables (EarthQuake and HiRiskEQ) are negative, suggesting a locational disamenity, as well as a nonlinear relationship between prices and risk exposure.

The high earthquake risk*time interaction variables were the main interests of this model. HiRiskEQxD2014 was omitted from the equation and acted as a reference point. There was no consistency in the sign of the interaction variable coefficients; only 6 of 17 coefficients were significantly different from zero at the 95% or 99% levels of confidence. Of the statistically significant coefficients, half of them were negative and half were positive. These outcomes may stem from data and/or categorization issues. Recall, Los Angeles' risk-based groups may not have been meaningfully differentiated and that it may not be possible to do so. Alternatively, investors may not be making a differentiation between the high and lower risk groups in Los Angeles. They may have recognized and accepted the risk, knowing that it can be mitigated through earthquake insurance.

Exhibit 12 displays the DiD estimation results for the second Los Angeles model. Model 2 utilized time periods instead of calendar years for the dummy time variables.

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Exhibit 12
Miami: Model 2 Difference-in-Difference Estimations

The results for the second Los Angeles model were similar to those of the first model. Again, there was no consistency in the sign of the coefficients for the interaction variables. The coefficients for HiRiskEQxDPeriod2005-2007 and HiRiskEQxDPeriod2020-2022 were both positive and significantly different from zero at the 90 and 99% levels of confidence, respectively. Holding all else equal, sales price is expected to be 8.8% higher for an apartment that sold in a high earthquake risk area in the 2020 to 2022 time period compared to the 2013 to 2015 time period. This unanticipated price premium may simply reflect the surge in apartment prices located in high earthquake risk zones during the COVID-19 pandemic.

Robustness Checks

In an effort to check the robustness of the Miami: Model 2 and Los Angeles: Model 2 empirical results, the data for each market was partitioned using the property number of units (PropNumUnit) variables. The analyses assumed a clientele effect where more sophisticated investors purchase larger properties. These same investors are believed to have a heightened awareness, recognition, and differentiation of hazard risks. These understandings are then assumed to be incorporated into their underwriting processes. These investors also insure these properties, and differences in insurance premiums are expected to play a role in their buying decisions. With this in mind, larger multifamily properties located in high natural peril risk areas are expected to have larger price discounts relative to their smaller apartment counterparts. In each cohort, high hazard risk apartments sold in the post-2014 period are also anticipated to have larger price discounts than their pre-2014 peers given that property investors are assumed to be more aware of natural hazard risks in the post-2014 time period. Unit size thresholds of 15 and 30 units were established for Miami and Los Angeles, respectively; these determinations were influenced by each metropolitan area's median value for PropNumUnit.

Exhibit 13 displays the Miami: Model 2 DiD estimations for the apartment size-based sub-samples.

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Exhibit 13
Miami: Model 2 Difference-in-Difference Estimations Partitioned by Units

For the larger unit number (PropNumUnit>15) sub-sample, all the interaction variable coefficients were negative; two of four coefficients were significantly different from zero at the 90% or 95% levels of confidence. The interaction variable coefficients for the PropNumUnit≤15 sub-sample all were negative and three of four coefficients were significantly different from zero at the 90% or 99% levels of confidence. The estimation results from the two sub-sample models did not support our expectation that large investors may have better awareness of potential risk exposure and were more sophisticated in pricing the risk. Larger and smaller apartments located in high hurricane risk areas had similar price discounts. Within each grouping, apartment price discounts in the pre- and post-2014 periods also had similar magnitudes. Overall, the results suggest that Miami apartment investors have long been attuned to high hurricane risk and priced apartments exposed to high risks accordingly.

Exhibit 14 displays the Los Angeles: Model 2 DiD estimations for the apartment size-based sub-samples.

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Exhibit 14
Los Angeles: Model 2 Difference-in-Difference Estimations Partitioned by Units

Focusing on the interaction variables, both sub-sample models lacked a consistency in the signs of their coefficients; few were significantly different from zero at the 90%, 95%, or 99% levels of confidence. The results failed to support the assertion that larger multifamily properties in high earthquake risk areas have larger price discounts relative to their smaller peers. There was also no evidence that apartments located in high earthquake risk areas sold in the post-2014 period have larger price discounts than their pre-2014 counterparts. Overall, the Los Angeles analyses lacked any meaningful results.

There may be several explanations for the lack of meaningful results from the Los Angeles models. First, as previously mentioned, the models may suffer from an identification issue related to the established threshold for high earthquake risk. Next, apartment investors may not meaningfully differentiate the risk between the unit-based groups, perceiving earthquake risk similarly across all of Los Angeles. Then, given that major earthquake events are infrequent, investors may simply be less concerned about the risk and its implications. Finally, investor worries may be mitigated due to availability of earthquake insurance. Many lenders require earthquake insurance for properties deemed to be in high, and even not so high, risk areas.

Conclusions

In conclusion, natural perils have had adverse economic impacts in Miami and Los Angeles. In Miami, hurricane wind and storm surge dominate risks, but inland flood from non-tropical cyclones and wildfire are additional risks. The high hazard areas subject to the highest hurricane winds and storm surge occur within 20 kilometers of the coastline. Climate change is expected to make these coastal locations more prone to higher winds and storm surge due to higher frequency of major hurricanes and higher sea level. Despite these elevated risks, there is currently no exodus from the shoreline due to its desirable location, but investors have been taking greater interest in inland areas due to its relatively lower hazard risk. In Los Angeles, earthquake dominates the risk from natural perils, but the metropolitan area is also subject to wildfire and inland flood risk. All areas of the Los Angeles metropolitan area are subject to earthquake risk, but the risk is highest inland near fault lines and on softer soils. While earthquake ground-shaking is not impacted by climate change, earthquake fire-following risk is impacted by climate change as it is expected to create more favorable conditions for fires.

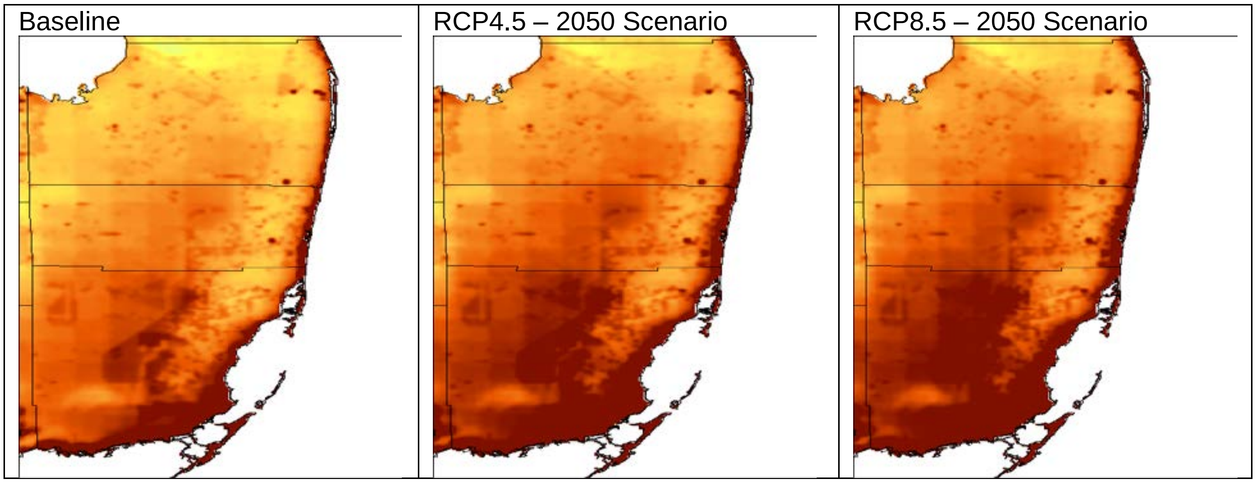
This study explores the price effects of natural peril risks. Specifically, it examines the impact of natural hazard risks on apartment sales prices in the Miami and Los Angeles metropolitan areas from 2005 to 2022. Given investors' increasing awareness of hazard risks, higher natural peril risks are expected to have placed downward pressure on multifamily property prices through time. High hazard risk apartments sold in the post-2014 period are also anticipated to have larger price discounts than their pre-2014 peers. Lastly, assuming a clientele effect where more sophisticated investors purchase larger properties, larger apartments located in high natural peril risk areas are expected to have greater price discounts relative to their smaller multifamily counterparts.

The Miami and Los Angeles results were in stark contrast to one another. For Miami, the hurricane risk variables displayed positive and nonlinear relationships with sales price; this was likely attributable to the greater desirability of their locations. The empirical results provided evidence of a consistent discount for apartments in high hurricane risk zones relative to their lower risk counterparts with apartment price discounts in the pre- and post-2014 periods having similar magnitudes. Larger and smaller apartments located in high hurricane risk areas also had similar price discounts. Overall, the results suggest that Miami apartment investors have long been attuned to high hurricane risk and have priced apartments exposed to high risks accordingly.

For Los Angeles, the estimated coefficients for the earthquake risk variables were negative, suggesting a locational disamenity. Overall, the empirical results failed to support any of the three expected assertions. The lack of meaningful results from the Los Angeles models may stem from a variety of reasons. First, the models may suffer from an identification issue related to the established threshold for high earthquake risk. Next, apartment investors may perceive earthquake risk similarly across all of Los Angeles. Then, given the infrequency of major earthquake events, investors may simply be less concerned about the risk and its implications. Finally, investor worries may be mitigated due to the availability of earthquake insurance.

Exhibits

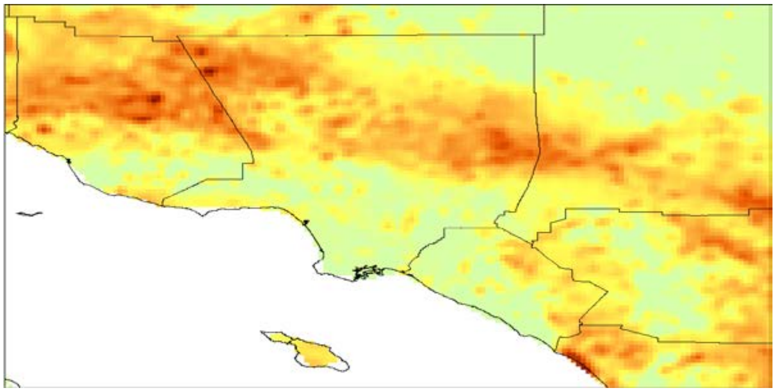
Exhibit 1
CoreLogic's Hazard Map for Miami



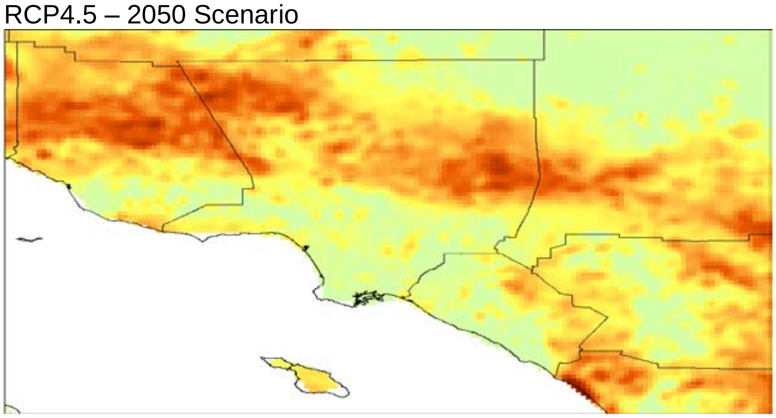
Sources: CoreLogic's RQE.

Exhibit 2
CoreLogic's Hazard Map for Los Angeles

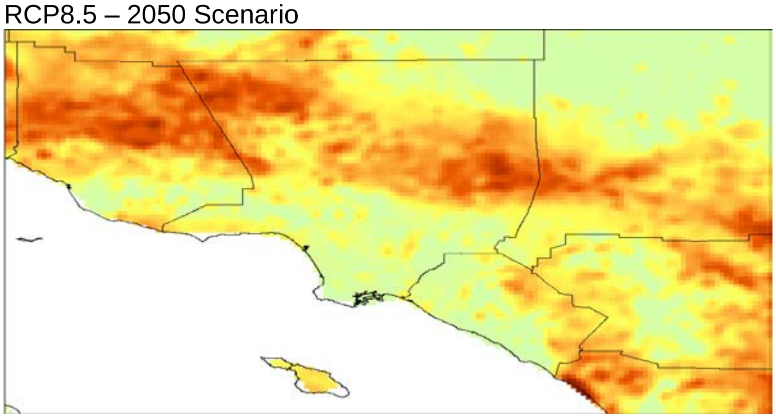
Baseline



RCP4.5 – 2050 Scenario



RCP8.5 – 2050 Scenario



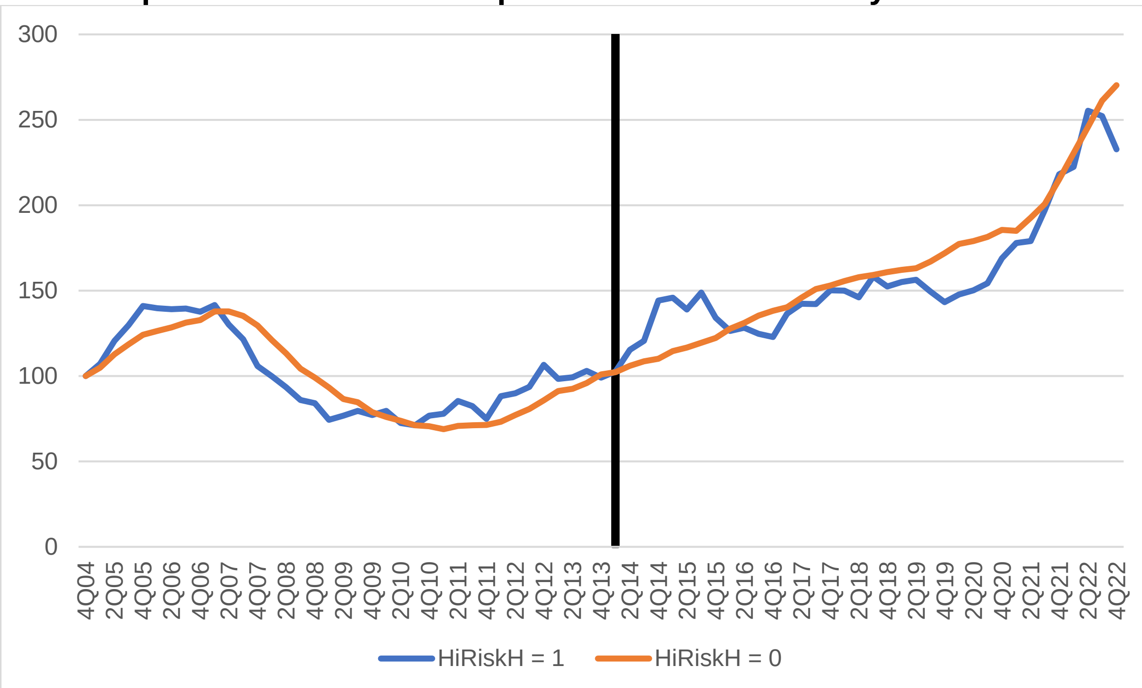
Sources: CoreLogic's RQE.

Exhibit 3
Apartment Transaction Activity for Miami and Los Angeles by Hazard Risks

	Miami		Los Angeles	
	HighRiskH = 1	HighRiskH = 0	HighRiskEQ = 1	HighRiskEQ = 0
Year	Total Volume ($) (n)	Total Volume ($) (n)	Total Volume ($) (n)	Total Volume ($) (n)
2005	301,457,157 (157)	784,952,410 (494)	1,433,246,845 (555)	9,411,062,076 (2,669)
2006	221,312,400 (110)	969,511,900 (366)	1,112,883,091 (432)	4,026,607,745 (1,783)
2007	90,324,900 (49)	450,937,700 (219)	1,264,953,014 (365)	5,573,404,830 (1,729)
2008	63,842,800 (51)	415,774,521 (175)	535,569,876 (237)	2,623,228,140 (1,126)
2009	80,435,365 (45)	382,135,367 (126)	335,382,185 (226)	1,625,146,416 (924)
2010	216,323,575 (96)	208,496,450 (126)	437,797,506 (228)	2,435,953,229 (1,071)
2011	170,317,679 (120)	455,795,679 (236)	637,944,193 (271)	3,497,320,124 (1,314)
2012	335,265,500 (149)	618,919,107 (365)	1,302,072,268 (389)	5,825,980,716 (1,789)
2013	337,392,300 (161)	571,840,743 (351)	1,139,762,401 (385)	5,335,633,297 (1,957)
2014	414,590,750 (183)	521,897,450 (377)	964,961,093 (366)	5,597,116,903 (1,937)
2015	434,529,200 (142)	1,276,817,280 (393)	1,243,012,147 (351)	8,521,523,253 (2,010)
2016	326,423,000 (114)	977,337,825 (349)	1,795,801,018 (397)	6,318,081,588 (1,921)
2017	242,445,150 (94)	1,267,097,600 (361)	1,686,679,281 (335)	9,657,628,594 (1,932)
2018	250,845,650 (83)	881,663,481 (305)	1,430,121,727 (313)	8,593,647,412 (1,792)
2019	315,320,700 (93)	977,794,936 (330)	1,360,601,918 (285)	8,668,415,091 (1,661)
2020	147,329,366 (78)	955,798,919 (286)	1,736,406,168 (238)	5,660,341,043 (1,238)
2021	840,301,050 (207)	2,378,616,867 (462)	1,519,076,519 (347)	7,703,035,670 (1,881)
2022	796,836,300 (178)	1,248,411,500 (361)	908,244,500 (208)	8,098,149,534 (1,525)
2005-2013	1,816,671,676 (938)	4,858,363,876 (2,458)	8,199,611,378 (3,088)	40,354,336,574 (14,362)
2014-2022	3,768,621,166 (1,172)	10,485,435,858 (3,224)	12,644,904,371 (2,840)	68,817,939,088 (15,897)
2005-2022	5,585,292,842 (2,110)	15,343,799,734 (5,682)	20,844,515,749 (5,928)	109,172,275,662 (30,259)

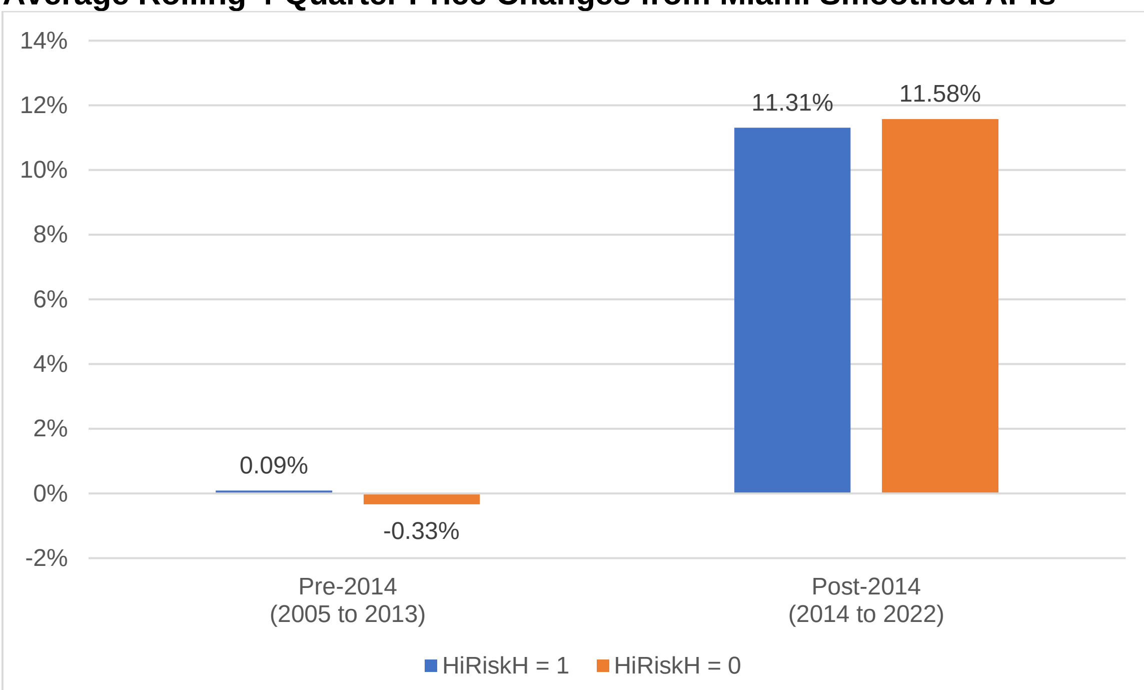
Sources: CoreLogic Public Record; Authors' calculations.

Exhibit 4
Miami Repeat Sales Smoothed Apartment Price Indices by Hurricane Risk



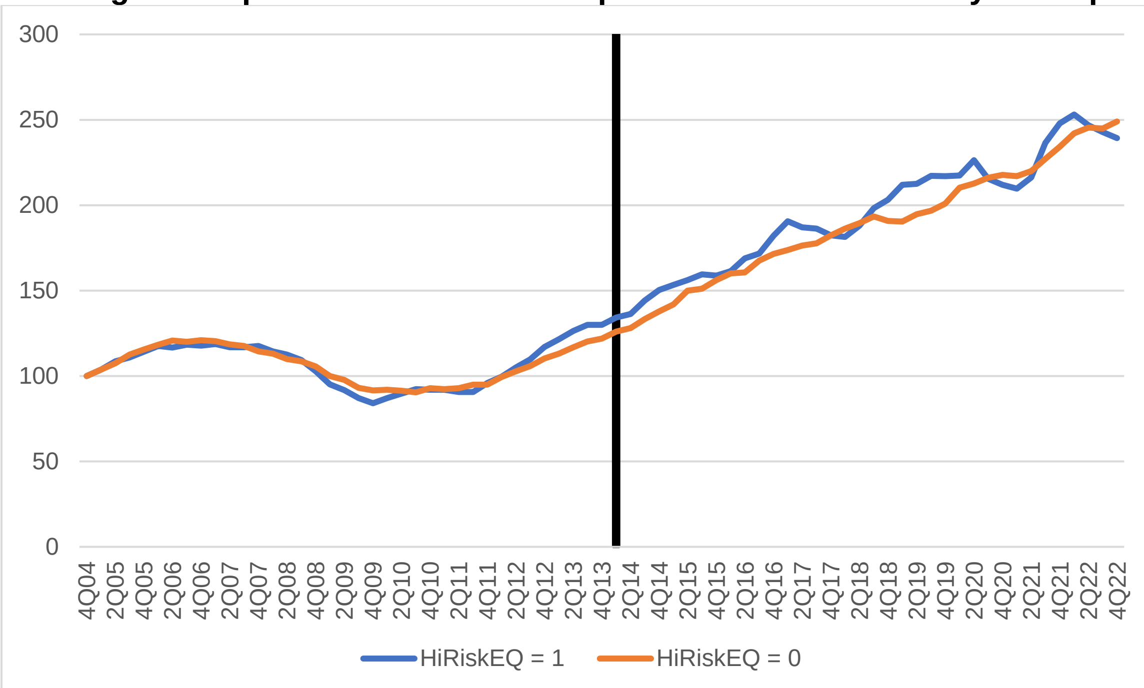
Sources: Authors' estimations using CoreLogic public record data.

Exhibit 5
Average Rolling 4-Quarter Price Changes from Miami Smoothed APIs



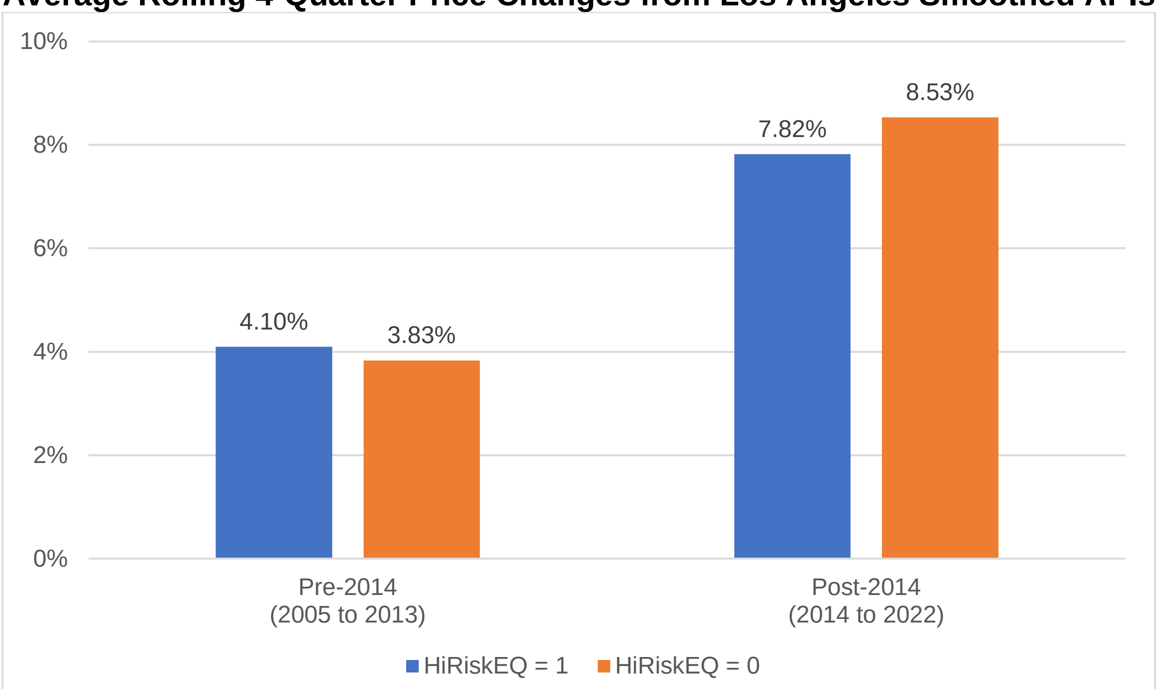
Sources: Authors' estimations using CoreLogic public record data.

Exhibit 6
Los Angeles Repeat Sales Smoothed Apartment Price Indices by Earthquake Risk



Sources: Authors' estimations using CoreLogic public record data.

Exhibit 7
Average Rolling 4-Quarter Price Changes from Los Angeles Smoothed APIs



Sources: Authors' estimations using CoreLogic public record data.

Exhibit 8
Descriptive Statistics

	Miami		Los Angeles	
	HiRiskH = 1 (n = 2,110)	HiRiskH = 0 (n = 5,682)	HiRiskEQ = 1 (n = 5,928)	HiRiskEQ = 0 (n = 30,259)
Variable	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
PropSP ($M)	2,647,058 (4,163,398)	2,700,422 (5,757,604)	3,516,281 (6,958,414)	3,607,927 (8,023,030)
PropNumUnit (Units)	14 (24)	22 (44)	19 (27)	15 (24)
PropSP/Unit ($/Unit)	223,055 (320,854)	155,234 (358,240)	204,944 (220,315)	263,841 (561,641)
PropLand (Acres)	0.2664 (0.3675)	0.6590 (1.6938)	0.4488 (0.8154)	0.3436 (0.6580)
PropAge (Years)	64.5336 (15.1607)	52.0593 (18.2889)	49.9084 (19.5603)	58.9544 (21.7290)
PropBltRatio	55.3077 (27.9687)	42.3012 (23.0969)	44.6776 (17.0607)	48.6708 (24.3481)
Ozone	0.0142 (0.1184)	0.1989 (0.3992)	0.2765 (0.4473)	0.1508 (0.3578)
HurricaneWind	1.2939 (0.2556)	0.7140 (0.1410)	-- --	-- --
EarthQuake	-- --	-- --	0.2657 (0.0336)	0.2046 (0.0312)
-- indicates not applicable				

Sources: CoreLogic; Urban Institute; Authors' calculations.

Exhibit 9
Miami: Model 1 Difference-in-Difference Estimations

Miami: Model 1 Dependent Variable: lnPropSP R^2 = 0.544 n = 7,792			
Independent Variable	Coefficient	Standard Error	
Constant	12.2012	0.1648	***
lnPropNumUnit	0.8940	0.0500	***
lnPropLand	-0.0679	0.0487	
lnPropAge	-0.1793	0.0203	***
PropBltRatio	-0.0062	0.0010	***
Ozone	-0.3142	0.0227	***
HurricaneWind	0.3916	0.0468	***
HiRiskH	0.3970	0.0676	***
D2005	0.0228	0.0472	
D2006	0.1742	0.0506	***
D2007	0.0499	0.0586	
D2008	0.0891	0.0631	
D2009	0.0425	0.0710	
D2010	-0.3875	0.0709	***
D2011	-0.2275	0.0572	***
D2012	-0.0988	0.0506	*
D2013	-0.0440	0.0511	
D2015	0.2775	0.0496	***
D2016	0.3215	0.0512	***
D2017	0.3532	0.0507	***
D2018	0.4654	0.0530	***
D2019	0.6156	0.0519	***
D2020	0.6609	0.0540	***
D2021	0.8787	0.0478	***
D2022	0.9770	0.0507	***
HiRiskHxD2005	-0.1338	0.0885	
HiRiskHxD2006	-0.2599	0.0972	***
HiRiskHxD2007	-0.2700	0.1252	**
HiRiskHxD2008	-0.5238	0.1259	***
HiRiskHxD2009	-0.7162	0.1347	***
HiRiskHxD2010	-0.2028	0.1120	*
HiRiskHxD2011	-0.1848	0.0991	*
HiRiskHxD2012	-0.2120	0.0913	**
HiRiskHxD2013	-0.1205	0.0902	
HiRiskHxD2015	-0.1290	0.0916	
HiRiskHxD2016	-0.0815	0.0968	
HiRiskHxD2017	-0.0380	0.1010	
HiRiskHxD2018	-0.1810	0.1054	*
HiRiskHxD2019	-0.2498	0.1019	**
HiRiskHxD2020	-0.4805	0.1077	***
HiRiskHxD2021	-0.2859	0.0846	***
HiRiskHxD2022	-0.3330	0.0884	***
Notes: With county and zip code fixed effects. *Significantly different from zero at the 90% level of confidence. **Significantly different from zero at the 95% level of confidence. ***Significantly different from zero at the 99% level of confidence.			

Sources: CoreLogic; Urban Institute; Authors' calculations.

Exhibit 10
Miami: Model 2 Difference-in-Difference Estimations

Miami: Model 2 Dependent Variable: lnPropSP $R^2 = 0.530$ n = 7,792			
Independent Variable	Coefficient	Standard Error	
Constant	12.2789	0.1643	***
lnPropNumUnit	0.8872	0.0505	***
lnPropLand	-0.0602	0.0493	
lnPropAge	-0.1731	0.0205	***
PropBltRatio	-0.0060	0.0010	***
Ozone	-0.3183	0.0229	***
HurricaneWind	0.3943	0.0471	***
HiRiskH	0.2989	0.0461	***
DPeriod2005-2007	-0.0030	0.0300	
DPeriod2008-2012	-0.1972	0.0303	***
DPeriod2016-2019	0.3511	0.0283	***
DPeriod2020-2022	0.7707	0.0296	***
HiRiskHxDPeriod2005-2007	-0.1043	0.0586	*
HiRiskHxDPeriod2008-2012	-0.2357	0.0545	***
HiRiskHxDPeriod2016-2019	-0.0419	0.0554	
HiRiskHxDPeriod2020-2022	-0.2169	0.0541	***
Notes: With county and zip code fixed effects. *Significantly different from zero at the 90% level of confidence. **Significantly different from zero at the 95% level of confidence. ***Significantly different from zero at the 99% level of confidence.			

Sources: CoreLogic; Urban Institute; Authors' calculations.

Exhibit 11
Los Angeles: Model 1 Difference-in-Difference Estimations

Los Angeles: Model 1 Dependent Variable: lnPropSP R^2 = 0.548 n = 36,187			
Independent Variable	Coefficient	Standard Error	
Constant	13.8832	0.0832	***
lnPropNumUnit	0.8327	0.0237	***
lnPropLand	0.0099	0.0228	
lnPropAge	-0.2991	0.0073	***
PropBltRatio	-0.0027	0.0004	***
Ozone	-0.1812	0.0090	***
EarthQuake	-0.6184	0.1062	***
HiRiskEQ	-0.0784	0.0365	**
D2005	-0.1780	0.0188	***
D2006	-0.2313	0.0207	***
D2007	-0.1760	0.0209	***
D2008	-0.1998	0.0236	***
D2009	-0.4554	0.0252	***
D2010	-0.3049	0.0240	***
D2011	-0.2728	0.0225	***
D2012	-0.1653	0.0207	***
D2013	-0.1036	0.0202	***
D2015	0.2359	0.0201	***
D2016	0.2389	0.0203	***
D2017	0.4152	0.0203	***
D2018	0.4763	0.0206	***
D2019	0.5452	0.0211	***
D2020	0.5356	0.0229	***
D2021	0.5559	0.0204	***
D2022	0.7044	0.0216	***
HiRiskEQxD2005	-0.0611	0.0464	
HiRiskEQxD2006	0.1072	0.0493	**
HiRiskEQxD2007	0.0557	0.0510	
HiRiskEQxD2008	-0.0350	0.0576	
HiRiskEQxD2009	-0.3005	0.0589	***
HiRiskEQxD2010	0.0329	0.0583	
HiRiskEQxD2011	-0.0760	0.0553	
HiRiskEQxD2012	0.0335	0.0503	
HiRiskEQxD2013	0.0729	0.0502	
HiRiskEQxD2015	-0.1385	0.0511	***
HiRiskEQxD2016	-0.0240	0.0499	
HiRiskEQxD2017	-0.0176	0.0517	
HiRiskEQxD2018	-0.0664	0.0527	
HiRiskEQxD2019	-0.1238	0.0540	**
HiRiskEQxD2020	0.1282	0.0572	**
HiRiskEQxD2021	0.1109	0.0514	**
HiRiskEQxD2022	-0.0693	0.0588	
Notes: With county and zip code fixed effects. *Significantly different from zero at the 90% level of confidence. **Significantly different from zero at the 95% level of confidence. ***Significantly different from zero at the 99% level of confidence.			

Sources: CoreLogic; Urban Institute; Authors' calculations.

Exhibit 12
Miami: Model 2 Difference-in-Difference Estimations

Los Angeles: Model 2 Dependent Variable: lnPropSP $R^2 = 0.536$ n = 36,187			
Independent Variable	Coefficient	Standard Error	
Constant	13.9019	0.0833	***
lnPropNumUnit	0.8351	0.0240	***
lnPropLand	0.0093	0.0231	
lnPropAge	-0.2932	0.0074	***
PropBltRatio	-0.0027	0.0004	***
Ozone	-0.1810	0.0091	***
EarthQuake	-0.6232	0.1075	***
HiRiskEQ	-0.1032	0.0220	***
DPeriod2005-2007	-0.2379	0.0117	***
DPeriod2008-2012	-0.3067	0.0116	***
DPeriod2016-2019	0.3669	0.0112	***
DPeriod2020-2022	0.5526	0.0125	***
HiRiskEQxDPeriod2005-2007	0.0483	0.0284	*
HiRiskEQxDPeriod2008-2012	-0.0345	0.0284	
HiRiskEQxDPeriod2016-2019	-0.0366	0.0283	
HiRiskEQxDPeriod2020-2022	0.0841	0.0322	***
Notes: With county and zip code fixed effects. *Significantly different from zero at the 90% level of confidence. **Significantly different from zero at the 95% level of confidence. ***Significantly different from zero at the 99% level of confidence.			

Sources: CoreLogic; Urban Institute; Authors' calculations.

Exhibit 13
Miami: Model 2 Difference-in-Difference Estimations Partitioned by Units

Miami: Model 2						
	PropNumUnit ≤ 15 Dependent Variable: lnPropSP $R^2 = 0.354$ n = 5,613			PropNumUnit > 15 Dependent Variable: lnPropSP $R^2 = 0.431$ n = 2,179		
Independent Variable	Coefficient	Standard Error		Coefficient	Standard Error	
Constant	12.6212	0.2075	***	14.5219	0.3946	***
lnPropNumUnit	0.7121	0.0694	***	0.3416	0.1170	***
lnPropLand	0.1617	0.0685	**	0.2531	0.1074	**
lnPropAge	-0.1739	0.0231	***	-0.2027	0.0410	***
PropBltRatio	-0.0006	0.0016		-0.0026	0.0018	
Ozone	-0.2428	0.0246	***	-0.4975	0.0506	***
HurricaneWind	0.4874	0.0508	***	0.2089	0.1043	**
HiRiskH	0.2708	0.0484	***	0.3602	0.1074	***
DPeriod2005-2007	0.0735	0.0327	**	-0.1271	0.0636	**
DPeriod2008-2012	-0.1319	0.0337	***	-0.3176	0.0620	***
DPeriod2016-2019	0.3586	0.0301	***	0.3872	0.0634	***
DPeriod2020-2022	0.7992	0.0314	***	0.7348	0.0671	***
HiRiskH X DPeriod2005-2007	-0.1166	0.0620	*	-0.1504	0.1341	
HiRiskH X DPeriod2008-2012	-0.2580	0.0582	***	-0.2348	0.1230	*
HiRiskH X DPeriod2016-2019	-0.0161	0.0578		-0.1466	0.1321	
HiRiskH X DPeriod2020-2022	-0.2226	0.0570	***	-0.2567	0.1244	**
Notes: With county and zip code fixed effects. *Significantly different from zero at the 90% level of confidence. **Significantly different from zero at the 95% level of confidence. ***Significantly different from zero at the 99% level of confidence.						

Sources: CoreLogic; Urban Institute; Authors' calculations.

Exhibit 14
Los Angeles: Model 2 Difference-in-Difference Estimations Partitioned by Units

Los Angeles: Model 2						
	PropNumUnit ≤ 30 Dependent Variable: lnPropSP $R^2 = 0.396$ n = 32,674			PropNumUnit > 30 Dependent Variable: lnPropSP $R^2 = 0.445$ n = 3,509		
Independent Variable	Coefficient	Standard Error		Coefficient	Standard Error	
Constant	13.6994	0.0894	***	15.0024	0.3352	***
lnPropNumUnit	0.8630	0.0262	***	0.5807	0.0938	***
lnPropLand	-0.0362	0.0251		0.3065	0.0838	***
lnPropAge	-0.2771	0.0079	***	-0.3611	0.0224	***
PropBltRatio	-0.0031	0.0005	***	0.0010	0.0013	
Ozone	-0.1841	0.0092	***	-0.1598	0.0387	***
EarthQuake	-0.5012	0.1112	***	-1.0140	0.3807	***
HiRiskEQ	-0.0912	0.0227	***	-0.1707	0.0805	**
DPeriod2005-2007	-0.2340	0.0117	***	-0.2670	0.0508	***
DPeriod2008-2012	-0.2983	0.0117	***	-0.3734	0.0497	***
DPeriod2016-2019	0.3579	0.0112	***	0.4542	0.0505	***
DPeriod2020-2022	0.5388	0.0126	***	0.7093	0.0578	***
HiRiskEQ X DPeriod2005-2007	0.0297	0.0294		0.1818	0.0999	*
HiRiskEQ X DPeriod2008-2012	-0.0160	0.0294		-0.0927	0.0999	
HiRiskEQ X DPeriod2016-2019	-0.0569	0.0292	*	0.0356	0.1018	
HiRiskEQ X DPeriod2020-2022	0.0695	0.0330	**	0.1159	0.1237	
Notes: With county and zip code fixed effects. *Significantly different from zero at the 90% level of confidence. **Significantly different from zero at the 95% level of confidence. ***Significantly different from zero at the 99% level of confidence.						

Sources: CoreLogic; Urban Institute; Authors' calculations.

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