Housing Supply and Natural Hazards Within and Across U.S. Cities

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This paper examines the link between housing supply restrictions and increased exposure to natural hazard risks in the United States. Overall exposure to natural hazard risk increases if housing supply is more elastic in riskier areas. However, evaluating this is complex due to the variety of hazards and their differing spatial correlations with housing supply. For example, wildfire risk is expected where the urban periphery meets flammable vegetation, while flooding risk is more likely along coasts. Moreover, housing supply restrictions could either encourage or discourage exposure to natural hazard risk at different levels. If, within cities, less elastic supply in safer areas leads to higher growth in at-risk areas, but riskier cities tend to be more stringently regulated, then restrictions would drive people to safer cities but also to the riskiest parts of those cities.

I show that urban growth has heightened exposure to natural hazard risk, considering a wide range of extreme climate threats. This exposure growth is driven both by the growth of the riskiest cities and the riskiest areas within cities. I find no evidence that strict housing supply regulations deter people from the riskiest cities. However, within cities, less elastic housing supply in safe areas leads to higher growth in at-risk areas. These findings complement those in Indaco and Ortega (2023) and Amornsiripanitch and Wylie (2023) by focusing on the geography of housing supply. In Ospital (2023), I argue that the distribution of land-use regulations within San Diego leads to increased exposure to wildfire risk. In this paper, I extend that argument by considering many hazards and all the U.S.

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I. Decomposing Growth in At-risk Areas Within and Between Cities

In this section I investigate the patterns of natural hazard risk exposure and housing growth in the United States. I show that there has been faster growth in areas more at risk, and that it has happened both between and within cities.

I measure the current risk of natural hazards using tract-level expected losses from FEMA's National Risk Index (NRI). I add up the expected losses in dollars per capita from 17 different natural hazards and then group tracts nationwide into quantiles of risk exposure. The NRI calculates Expected Annual Losses (EAL) by multiplying exposed values by a hazard's annual frequency and historical loss ratios. This is done separately for population loss (monetized using a Value of Statistical Life approach) and for the value of exposed buildings. To arrive at expected losses per capita, I divide the EAL for buildings and people by the population of the tract. This final step ensures that my measure of risk is not mechanically influenced by the sheer number of buildings or people at risk.[1]

Over the past decades, housing growth has disproportionately happened in areas of the United States with the highest natu-

[1] The 17 hazards are: Avalanche, Coastal/Riverine Flooding, Cold/Heat Wave, Earthquake, Hail, Hurricane, Ice Storm, Landslide, Lightning, Strong Wind, Tornado, Tsunami, Volcanic Activity, and Wildfire. The data sources vary by hazard, but the periods considered in the calculations of frequencies and loss ratios end in 2021 at the latest. Tract populations are measured as of 2016, and buildings are valued based on 2018 valuations from the 2010 Census. The NRI also reports EALs for agriculture, but I omit those due to the urban focus of this paper. I exclude Drought because, in the data, it only affects agriculture, not people or buildings. The inflation-adjusted Value of Statistical Life used by FEMA treats each fatality or ten injuries as $7.6 million of loss in 2020 U.S. dollars.

ral hazard risk, but in recent years, fewer new homes have been built in the riskiest places. I combine the natural hazard risk from FEMA with housing unit counts from the Census and the American Community Survey, as reported in the Longitudinal Tract Data Base (LTDB). Of the 61.2 million homes added since 1970, 13.9 million (22.7%) are in the 20% riskiest census tracts in the country, as measured by expected losses. A total of 27.4 million (44.8%) homes were added in the top 40% riskiest census tracts. I we consider more recent changes since the year 2000, the relationship is not monotonic: the number of homes has increased more in the second and third quintiles of expected losses, and less so in the top two quintiles of expected losses.

Next, I perform exact decompositions of housing growth to explore whether this aggregate increase in exposure is due to more homes being built in risky cities or to more homes being build in riskier parts of the city. Specifically, I define the national exposure to natural hazard risk ε_t^r as the fraction of the total housing stock that is on tracts in quantile r of expected losses. Then I decompose the change in national exposure into three components:

$$\begin{aligned}\Delta\varepsilon^r = \; & \underbrace{\sum_{c\notin \text{New}^r} h_{ct-1}\Delta\varepsilon_c^r}_{\text{Within cities}} \\ & + \underbrace{\sum_{c\notin \text{New}^r} \Delta h_c \left(\varepsilon_{ct}^r - \varepsilon_{t-1}^r\right)}_{\text{Across cities}} \\ & + \underbrace{\sum_{c\in \text{New}^r} h_{ct} \left(\varepsilon_{ct}^r - \varepsilon_{t-1}^r\right)}_{\text{New development}},\end{aligned} \tag{1}$$

where $\Delta x \equiv x_t - x_{t-1}$ indicates changes in any variable x_t measured in year t, h_{ct} is city c's share of national housing stock, ε_{ct}^r is city c's share of housing stock at risk r, and $\text{New}^r \equiv \left\{c : \varepsilon_{ct-1}^r = 0\right\}$ is the set of cities that did not have homes exposed to expected losses in quantile r in the initial period.[2]

The "Within" component of the decomposition represents the change in exposure that would have resulted had relative city sizes been fixed, but city-level exposure shares evolved as in the data. That is, it captures whether more homes are going to the riskiest parts within cities. The "Across" component captures aggregate changes due to changes in the housing distribution across cities. The "new development" component captures aggregate increases in exposure due to homes built in risky tracts that where initially undeveloped. Subtracting the initial national exposure $\left(\varepsilon_{t-1}^r\right)$ captures that the contribution of newly-developed tracts to aggregate exposure changes can be positive or negative, depending on whether the risk exposure of the new tracts is above or below the old national level.

The top row of Figure I shows the change in national exposure (the left-hand side of the decomposition in Equation 1) considering 1970-2017 changes in Panel A and 2000-2017 in Panel B. As a result of the new flow of homes since 1970, a greater fraction of the housing stock is now on the riskiest places. The same pattern emerges if we instead consider more recent changes since 2000, except that the relationship again is not monotonic at the top: while the fraction of homes in the riskiest quintile has increased, it has increased by less than the one in the second-to-riskiest group of tracts.

The results of the decomposition indicate that all three margins significantly impact natural hazard exposure. Focusing first on the long-term changes from 1970 (Panel C), all three margins contribute to the growth of the two riskiest quintiles. The cross-city component and new development were particularly important for the growth of the two riskiest groups of tracts, especially the top quintile. The "Within" component, on the other hand, contributes most to the growth of the fourth quintile and not much to the top quintile. When applying the decomposition with 2 instead of

[2] I define cities as Core-Based Statistical Areas (CBSAs) or Combined Statistical Areas (CSAs) of adjacent CBSAs, based on economic ties measured by commuting patterns. This captures overlapping labor markets, making tracts closer substitutes for each other within a city, and cities substitutes for other cities.

5 risk quantiles, we find that exposure to above-median expected losses increased by 9.1 percentage points, with the "Within" component accounting for 30.3% of the increase, the "Across" component accounting for 39.4%, and the "New" component for the remaining 30.3%.

In the more recent period from 2000 to 2017 (Panel D of Figure I), the margin of new development is irrelevant because virtually all tracts were already developed in 2000. In this period, the non-monotonic pattern of the within-city component accentuates, to the point where it contributes *negatively* to the growth of the riskiest quintile. Applying the decomposition with 2 risk quantiles, the "Within" component accounts for 19.7% of the increase in exposure to above-median expected losses. The "Across" component accounts for the remaining 80.3%.

II. Housing Supply Regulation Stringency Across Cities

In this section, I describe how the cross-city components of exposure growth obtained in the previous section are related to the stringency of regulation restricting housing supply. To measure regulation, I use the survey-based Wharton Residential Land Use Regulation Index from Gyourko, Hartley and Krimmel (2019).

I proceed by plotting exposure-weighted city growth in 2000-2017 against the Wharton Index (Figure I, Panel E). The former correspond to the city-level elements of the cross-city component in the decomposition formula: $\Delta h_c \left(\varepsilon^r_{ct} - \varepsilon^r_{t-1}\right)$. I further divide them by the total exposure change $(\Delta\varepsilon^r)$, so the points add up to the "Between" term in Equation 1. The Wharton Index is only available for 44 cities, so I grouped the ones remaining and plotted their sum with a value of zero, which by construction is in the middle of the distribution. I focus on the most recent period of 2000-2017 to be closer in time to the Wharton Index. To have a single measure of exposure, I repeat the decomposition but with 2 quantiles instead of 5 quantiles, so again ε_t measures the fraction of homes exposed to above-median expected losses.

The figure shows no evidence of strictly regulated cities offsetting the aggregate increase in natural hazard risk exposure. On the one hand, we see some cities with lax regulations, such as Cleveland or Detroit, contributing to the national increase, and other more strictly regulated cities, such as Phoenix or San Francisco, offsetting the national trend. These examples would be consistent with a scenario where strict regulations keep people away from the riskiest cities. However, we also have the counterpoint of Los Angeles and New York, both strictly regulated, contributing significantly to aggregate exposure.

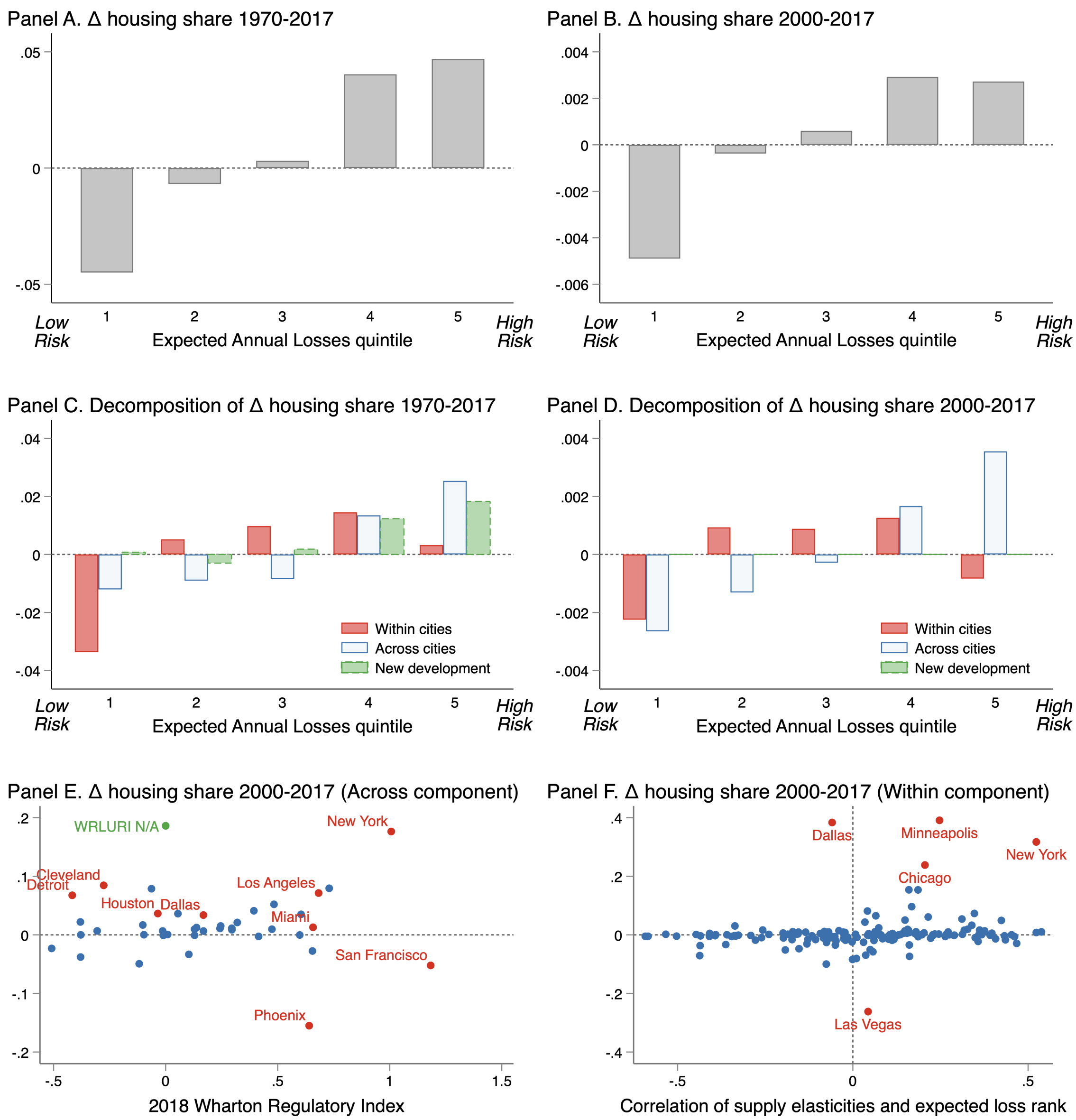
III. Housing Supply in the Safest Areas Within Cities

In this section, I show that growth in risky areas was higher in cities where areas with lower natural hazard risk had a less elastic housing supply. To do so, I extend the data with census tract–level estimates of housing supply elasticities from Baum-Snow and Han (2021).[3]

As a first pass, I calculate the correlation between the price elasticity of housing supply in 2001 and the rank of expected losses for each city. Panel F of Figure I shows a scatter plot of these correlations (on the x-axis) against the within-city elements from the growth decomposition (on the y-axis). As in the previous section, I focus on the most recent period of 2000-2017 and consider exposure to above-median expected losses from natural hazards. There is no apparent relationship between the variables when the correlation of elasticities and risk is negative, but a positive one when the correlation becomes positive. This means that the within-city component of growth in national exposure is driven by cities where the riskiest tracts have more elastic sup-

[3] I use their linear IV estimates. I set the elasticities that are estimated to be negative equal to the minimum non-zero estimate. I prefer this approach over excluding the negative elasticities because the goal of this exercise is to study the effect of having safe areas with low elasticities. However, tracts with constrained supply likely have less price and quantity variation, making it difficult to estimate a precise small number.

FIGURE 1. DECOMPOSITION OF GROWTH IN NATIONAL FRACTION OF HOMES AT RISK FROM 1970-2017 AND 2000-2017.



ply, such as Chicago, Minneapolis, and New York. However, we must note two outliers: Dallas, with low correlation and large exposure growth, and Las Vegas, with low correlation and low exposure growth.

Next, I run regressions of the growth in number of homes since 2000 on housing supply elasticities in the year 2001 and the current distribution of natural hazard risk:

$$\begin{aligned} \Delta \ln H_i = \quad & \alpha R_i + \beta R_i \overline{E}_{c(i)}^{Safe} \\ & + \gamma R_i \overline{E}_{c(i)}^{Risky} + \mu_{c(i)} + e_i, \end{aligned} \tag{2}$$

where i indexes census tracts and $c(i)$ the city where tract i is located. The left-hand side is the change in log housing units between 2000 and 2017. The variable R_i is a dummy indicating that the tract is among the top 50% riskiest in the country. The variable $\overline{E}_c^{Safe}$ is the average housing supply elasticities among safe tracts in the city (i.e., $R_i = 0$), and $\overline{E}_c^{Risky}$ the average among risky tracts. Finally, μ_c is a city fixed effect, and e_i is the residual.

The coefficient β measures how housing growth changes if the price elasticity of housing supply in the safe parts of the city is increased, and the presence of a city-level fixed effect means that the comparison is using only variation within cities. Controlling for the average housing supply elasticity across all risky tracts in the city helps ruling out differential trends in the growth of risky places in cities that are more or less elastic.

I estimate the regression by OLS and cluster standard errors at the level of the CSA by the risky-place indicator. I obtain an estimate $\hat{\alpha} = -0.013$ (s.e. 0.024), not significantly different from zero. The estimate $\hat{\beta} = -0.121$ (s.e. 0.054) means that reducing the housing supply elasticity of safe places by one standard deviation (0.145) leads to riskier tracts growing by 1.8% more than the safer ones. The coefficient on the interaction with average elasticity in risky areas has opposite sign $\hat{\gamma} = 0.130$ (s.e. 0.078), as expected, since housing growth is a function of it by construction. Taken together, the estimates predict that risky places will grow more than safe places when the average safe-place elasticity is greater than the risky-place elasticity by 0.022. The cross-city median difference between safe and risky area average elasticities is 0.025. As further illustration, New York and Kansas City have similar observed average elasticity in risky places (0.435 and 0.443), but the safe-area elasticity of New York (0.191) predicts that risky areas grow 4.7% more than safe areas while the one of Kansas City (0.436) predicts that risky areas grow only 1.7% more.

IV. Conclusion

Exposure to natural hazard risks in the U.S. grew due to the growth of the riskiest cities and the distribution of housing growth in the riskiest areas within cities. Across cities, there is no evidence that strict housing supply regulations are keeping people away from the riskiest cities, although the data is coarse. However, within cities, less elastic housing supply in safe areas is associated to higher growth in at-risk areas.

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