How Climate Change Can Affect Where People Live? Evidence from Flood Surprises

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Abstract

This paper examines the extent to which flood-risk revisions, on their own, can affect the size of the community and real estate values over time. I compile a new measure of insured and uninsured losses for 4,147 communities and identify relatively small flood events that occur in places with different flood history. I show that flood history determines the extent to which events are anticipated and covered by insurance. Only locations with flood surprises experience declines in population. These occur in attractive communities with high pre-flood growth where real estate prices do not compensate for higher flood risk. Flood surprises in communities where housing prices decrease and compensate for higher risk have stable population.

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Real Estate, Natural Disasters

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1 Introduction

Flooding is a frequent concern across the US since damage to buildings and equipment is hard to reverse. The US Government maintains a subsidized flood insurance program which conveys local risk through designated flood zones. Changes in climate, local development, and outdated prevention can shift risk beyond these zones, prompting households to learn about risk through experience and update their expectations. Insurance take-up jumps after floods either by rational choice or by relief requirements (see Gallagher 2014, Kousky 2017). This implies that flood-prone places tend to be insured, while low flood-history places increase take-up after risk revisions. Additionally, a sizable impact on the housing stock or productivity can decrease the size of the community, at least in the short term. While health hazards have been shown to affect population and house prices (see Banzhaf and Walsh 2008, Kahn 2010, Davis 2004, Greenstone and Gallagher 2008), there is little evidence that flood hazard has a consistent impact, particularly in the absence of confounding housing or productivity effects.

This paper examines the extent to which flood-risk revisions, occurring in the absence of housing supply or productivity shocks, can affect the size of the community and real estate values over time. The effect of a higher risk can be minimized through insurance. Yet, this raises the cost of living in the community, either directly by new zoning requirements or by rational choice. Additionally, there are other costs such as foregone wages and temporary relocation expenses which are not insurable. Higher risk can, therefore, make a location less attractive compared to other places with similar characteristics but unchanged flood risk. Durability of houses already in place, as in Glaeser and Gyourko (2005), ensures that when risk increases, following smaller floods, population will be stable – house prices will compensate for the insurance cost. However, in the case of growing communities with new construction, higher risk can delay land development and increase house prices (Capozza and Helsley 1990). Homes in these communities are also likely to have higher price-to-cost ratios, which encourages investments in home improvement, further increasing house prices after a flood (Gyourko and Saiz 2004). As a result, newcomers, who choose among a set of destinations, may steer away. Higher flood probability can, therefore, affect the size of the community, especially if it has been an attractive destination prior to the risk revision.

I evaluate the responses of population and housing after risk revisions related to unusual but small flooding. Expectations are the main driver since damages are not sufficient to affect the house supply or local productivity (95^{th} percentile is 0.87% of real estate value). I utilize a new dataset of insured and uninsured damage for 4,147 communities in 38 states between 2003 and 2013 that allows for consistent comparison. The number of structures fully destroyed in a location in the past 25 years allows me to separate low from high flood-history communities – below the state median (alternatively with zero prior destruction) are considered low history. The main results compare population and house price changes conditional on flood history. Even after conditioning on flood history, some locations can be attractive destinations with significant population growth, due to the presence of human capital (Glaeser et al., 1995) or other amenities (Glaeser et al., 2001). Since booming and declining communities experience contrasting housing and productivity conditions, risk revisions can have different impact. To account for this, I further divide locations based on their pre-flood growth. Finally, I examine the regional heterogeneity of the national results, the risk spillover to neighbors, and the role of local social capital.

The evidence suggests that flood history is related to local perceived flood risk. Locations with high flood history have a higher footprint in a flood zone, more insurance purchases, and a higher insurance coverage. They have almost 25% higher insurance payouts after a flood, even when controlling for total losses. This likely reflects not only the higher number of people required by the flood zoning to purchase insurance but also the higher perceived risk in the proximity. It also suggests that flooding occurs mostly within the established flood zone. Population and house values in these communities are not affected after flooding.

Places with low flood history depend less on insurance – they have less people in a flood zone, less active policies, and lower total coverage. This suggests that when floods do occur they are not widely expected and constitute surprises. Smaller payouts after events indicate that floods occur outside the flood zone or that insurance take-up within the zone is small. In a simple specification, population in the year following the event declines by 0.3% relative to a fixed effect and a linear trend. This effect is persistent and also includes a break in the pre-flood trend, which has a significant long-term impact on population when compounded. Including controls for composition of the damage and community characteristics increases these effects substantially: 1.2% drop on impact and 0.6% drop in pre-flood trend. The population effects are mostly driven by attractive communities with positive pre-flood growth. They see a persistent 1.4% dip in population with a 0.7% decrease in the pre-flood trend. Non-growing communities do not lose population. Instead, they see close to a 4% drop in real estate values, with the biggest effect among higher tier housing, which is likely closer to water. This is consistent with evidence from Glaeser and Gyourko (2005) where adjustments in house values can limit population changes. Interestingly, house prices do not decline in the attractive communities, only population growth is affected. This is consistent with the model of Capozza and Helsley (1990) where higher uncertainty delays new construction and increases its price. The combination of higher price for new construction and lower demand for new housing can explain the fact that real estate prices remain unchanged. Alternatively, population-driven decline in demand for housing may not affect prices if owners of existing houses invest in substantial home improvement after flooding. This is likely to be the case in growing communities where price is above replacement cost as shown by Gyourko and Saiz (2004). Finally, regional evidence shows that the population decline in attractive communities after a flood surprise is a general phenomenon across the nation.

All together, the results suggest the following interpretation. Flood surprises increase expected probability of a future flood which in turn raise the cost of living. In locations where demand for housing is low existing structures are sold at a discount that covers the additional cost. This appears to be sufficient to maintain the existing population trajectory. In locations where demand for housing is high increasing risk delays/increases the price of new construction, which drives new movers to other destinations.

Climate change will likely cause some significant flood events but, more importantly, it will also change expected risk across a much wider set of communities. The evidence here helps understand how risk affects where people live and how much they pay for housing. Historical flood experience results in the institution of local preventive measures such as zoning, which requires mandatory insurance coverage. Consequently, additional flooding is in line with expectations and only generates insurance payouts. Flood surprises, on the other hand, deviate from expectations and raise flood risk. In the cases when damage is limited, higher risk does not just force higher insurance purchases, as shown previously in the literature, it also reduces the total number of people that choose to live there. The attractiveness of the community determines the ultimate impact of surprises: strong demand for new housing means that population is mostly affected; weaker demand implies that house prices are mostly affected. The evidence in the paper also emphasizes that a general economic analysis of the impact of natural disasters has to account for changes in perceived risk, particularly where damages are small.

This paper can be placed within several different literatures. First, it is related to the vast literature on local outcomes, which examines factors that cause the rise and fall of the economic status of different communities. Within this literature Moretti (2011), Diamond (2014), and Notowidigdo (2011), among others, use the concept of the spatial labor market equilibrium and focus on the effect on productivity or amenity shocks on local population, wages, and house prices. I emphasize the impact of changes in expectations related to amenities and, therefore, build on insights from Topel (1986). I further show that durable housing, as originally discussed by Glaeser and Gyourko (2005), is key in understanding why flood-risk shocks have asymmetric impact across growing and declining locations. A different set of papers, reviewed by Rosenthal and Ross (2015), more generally study what causes population and economic differences across communities. Davis (2004), Banzhaf and Walsh (2008), and Kahn (2010) examine the effect of local health risks on population and housing. The former finds compensating declines in real estate values, while the latter two find a positive association between population and health risk.

The paper is also related to the literature on natural disasters. This literature mostly focuses on the effect of hurricanes at different geographical levels and measures damage in a variety of ways. The current study also includes hurricanes since they produce significant flood damage. Strobl (2011) uses wind speed as a proxy for damage and finds that hurricanes lower county GDP by 0.5% and do not change total population but affect its composition. Deryugina (2017) uses hurricane paths and simulation estimates of damage to examine the disaster and non-disaster transfers to affected communities as well as the effect on demographic and economic variables. She finds that population is not affected. Both papers utilize county-level data based on estimates of damage based on hurricane locations. I use community-level losses that are consistently imputed by federal agencies and do not rely on associations between wind speed/hurricane path and damage. Importantly, I show how important historical flood experience or flood preparedness is for how communities are impacted. The papers in this literature emphasize the effect of total damages, while I focus on locations where there are more uninsured losses. The response of the real estate market has been studied extensively within this literature. Bin and Polasky (2004) focus on one county and one hurricane and find price declines within the flood plane. Hallstrom and Smith (2005) focus on a different county and show that a "near miss" hurricane still lowers prices in the flood plane. Murphy and Strobl (2010) find that coastal cities see increases in house values after hurricanes. My paper provides evidence based on a considerably larger sample and focuses on overall prices in the community.

Finally, this paper is related to the literature on expectation formation and learning after rare events. It is close to Gallagher (2014) which examines the change in insurance take up after flood events. The paper concludes that flood events lead to revisions of perceived risk which lead to higher insurance purchase that is not very persistent. The evidence is complementary to my findings since it suggests that living in flooded communities becomes more expensive.

The rest of the paper is structured as follows. Section 2 discusses the institutional details of the flood insurance program and describes how the flood data was compiled. Section 3 presents the main results. Section 4 examines the regional heterogeneity of the main results. Section 5 includes extensions and robustness and Section 6 concludes the paper.

2 Flooding Dataset and Institutional Details

Flood insurance in the US is administered by the federal government through the National Flood Insurance Program (NFIP). The program makes insurance available at communities – cities, towns, townships, counties – that maintain a flood zone map and enforce local building code. The map delineates Special Flood Hazard Areas (SFHA) with varying degrees of flood risk. Two general SFHAs are the 100-year and 500-year flood zones where flood is expected to occur with certainty every 100/500 years respectively. The risk within the 500-year SFHA is not uniform – areas close to the 100-year zone will have a higher risk of flooding if the geography is similar. Insurance purchase is mandatory for structures within the 100-year zone but not required elsewhere. This is important because risk expectations rather than local regulation will determine the insurance purchase outside of the 100-year zone.

The flooding dataset is based on information from NFIP on insured damage and from FEMA/Small Business Administration (SBA) on uninsured damage. The sample includes 38 US states which feature disaster declarations related to flooding. The level of aggregation is at the community level which includes 4,147 distinct location with median size of 34 thousand people. The insured damage is matched to actual disaster declarations which, in turn, are associated to uninsured damages. In only 75% of community/year cases total losses are based on insured and uninsured damage. All together, total damage in the data has four components: insured individual/business from NFIP; uninsured individual from FEMA and SBA; uninsured business from SBA; uninsured public from FEMA. In this paper

I focus primarily on total damage. The components are only used to control for events where most of the damage comes from one of the source. Additional information about the data is provided in Appendix A2. Finally, I have limited information on total insurance policies and total coverage for a subset of years in the sample.

Population information comes from the annual US Census estimates for cities and towns. The geographical detail of this data maps directly into the community level of the flood damage data. Locations with less than fifteen thousand people are combined with the county balance areas to make sure that results are not driven by very small settlements. Real estate information comes from the Zillow service and is available at the zip-code level. It provides estimates of house values separated into three tiers. These are calculated by splitting the price distribution of all housing into three parts and reporting the middle point of each. Any zip-code level information is imputed to the level of the community by using census-block-based population weight for each zip code. The rest of the information used in this paper comes from the 2000 US Census data at the block-group level.

The paper identifies floods according to the relative size of the damages. Cases where more than 0.01% of the total real estate value of the community is destroyed constitute a flood event while the rest are censored. I focus on a wide spectrum of events because relative damage is context specific – less destructive floods can have significant impact on perceived risk if they occur in areas with no flood history. I also replicate the main results in the paper using a cut-off of 0.02% (the 25^{th} percentile) and after dropping locations with damage over 8.66% (the 95^{th} percentile). These are listed in the online appendix.

The first panel of Figure 1 shows all communities that flooded between 2003 and 2013. Flooding appears to be widespread across the country and not only a coastal phenomenon. In the interior major floods result from significant rain or snowmelt which causes rivers and creeks to spill in the surrounding areas. Some of the communities in the sample experience repeated disasters during the sample period. I will separate these into a different category since their event study explicitly includes an interim period. Furthermore, the fact that these places flood so frequently suggests that they are fundamentally different from the rest of the cases. One example of this is the really high footprint in a flood zone as shown in the summary statistics. The second panel of Figure 1 shows single and multiple flood locations. There are about three times more single than multiple hit places (1,519 vs 542). A significant portion of the latter are located by the coast while the former are more uniformly distributed.

I identify flood surprises using the total number of housing structures that were completely destroyed due to flooding between 1978 and 2003. Note that I have information on total dollar amounts paid since 1978 but this is not ideal since without proper historical discounting this cannot be compared across locations. The number of buildings completely lost to flooding, on the other hand, is readily comparable between communities. I further normalize this number by the total building structures and compare to the state median across all location that experience a flood. Communities below the median are considered low-risk and flood event is assumed to generate a higher surprise than the rest. Using the median ensures that there are sufficient number of places which can be placed within each category and that the distinction between high and low surprise is region specific. In an alternative specification, I assume that high surprise are only communities with zero lost structures. While this reduces the number of high-surprise communities it ensures that observed floods are not consistent with the historical experience. The main results do not change substantially with this specification.

The second panel of Figure 2 separates the high/low surprise locations. These tend to be contiguous suggesting that flood surprises occur when a flood extends beyond a high-risk area and into a low-risk one. High-risk areas also tend to be contiguous to multiple-flood areas which reinforces the assumption that the former are at a generally higher risk of disaster. The map also confirms that high/low surprise locations are relatively close and are part of the same economic area.

Table 1 list summary statistics for location according to number of floods. Table 2 lists summary statistics for important location categories. Note that for the case of single floods the 95^{th} percentile of relative damage is 1.55%. This confirms that the flood shocks have a minimal effect of supply of housing and that any effect they have should run through risk revisions. Locations that experience significant relative damage are those with multiple floods in the sample. The number of no-flood and single-flood places are closely matched (1771 vs 1519). This reflects the fact that the sample includes 38 states and that flooding is a widespread phenomenon. These groups have similar population, income, growth, and housing values. The no-flood group has smaller footprint in a flood zone and less active insurance policies. When we look at single-flood places with low historical flooding (high surprise) we see that the no-flood group becomes closer to the single flood group. The communities with high/low flood surprise differ on important characteristics driven by their different historical experience. The latter have higher damage, higher insured damage share, more people in a flood zone, higher historical destruction, more insurance policies. These differences emphasize the extent to which high-surprise locations do not anticipate flooding. Comparing relative damage and fraction of population in a flood zone, we can see that the high-surprise communities likely experience damage outside the flood zone while for the low-surprise communities the observed damage is within the flood zone. Comparing high-surprise communities by pre-flood growth reveals that the two groups are similar but for the difference in real estate values which reflect their attractiveness.

3 Main Results

One of the main results in the paper is that the extent to which disaster damages affect a community is determined by its historical experience. Flooding at communities with low flood history constitutes a surprise which increases expected future risk and raises the cost of living in such places. To set the stage for the formal results, consider the experience of three communities in Connecticut: Milford, Bridgeport, and New Haven. All were affected by hurricane Irene in 2011 and Sandy in 2012. Since the events were consecutive they fall in the single-flood group with no interim period. Milford made it into the local news for the extent of losses and the fact that no one had the intention to move. It suffered \$90 mil in damages (0.5% of real estate value) while Bridgeport and New Haven suffered \$16 mil (0.12%)/\$7 mil (0.05%). The difference in damages implies that Milford should be affected significantly more but its flood history suggests that the event was not such a surprise. Between 1978 and 2003 Milford lost 6.2% of its structures due to flooding while Bridgeport and New Haven lost 0.7%/0.5% respectively. Figure 3 shows the population growth for each of the communities. We see that the population in Milford was not affected. At the same time the communities with smaller overall damage but with relatively low history of floods experienced population declines. Notice that the communities did not experience a large-scale disaster since damages were relatively small. Nevertheless, they seem to have changed the expectations about future flood risk and the attractiveness of the communities with low history.

Flood Surprise and Insurance Payouts

The first set of formal results examine the extent to which historical flood losses can be used to identify flood surprises. Regulations require that structures within the 100-year flood zone carry insurance if they have a federally-backed mortgage. Insurance purchase for any other structures will depend to some extent on the perceived risk of a flood. High flood history increases perceived risk and leads to insurance purchase. I examine this relation by comparing the average insurance payouts across the high/low flood history groups in the cross-section of all events. In particular, I test whether a given amount of total damage (insured and uninsured) generates more insurance payouts in locations with historical exposure to flood events i.e. low-surprise communities. I estimate:

$$\ln\left(Payouts\right)_i = \alpha_t + \beta F_i \times Dam_i + \gamma F_i \times Dam_i \times LSurprise_i + \{MFl\} + \epsilon_i \tag{1}$$

where $Payouts$ is total insurance payouts per capita after an event at community i and α_t is an year effect. F_i is an indicator for a flood at a single-flood location i, Dam_i is total damage per capita (insured+uninsured), and $LSurprise_i$ is an indicator for low surprise flooding (high flood history). $\{MFl\}$ abbreviates the same set of indicators for locations with multiple floods. Positive γ implies that higher overall damage leads to more insurance payouts at places with high history of flooding relative to places with low history. I estimate two variants of the model above: with and without controlling for total damage. In the latter case γ represents how much more insurance payouts are generated during an average flood event at a communities with history of flooding. It is possible that an average flood event in these communities is much more destructive so I control for total damage. Finally, I also estimate the model using active insurance policies for the set of communities where this data is available.

Table 3 shows the estimation results. Communities with a low-surprise flood i.e. high flood history have a significantly higher insurance payouts per capita during an average flood event. This is consistent with the higher number of active insurance policies observed. These locations receive almost double the insurance compensation after an event compared to locations with low previous experience with flooding. Column 2 of Table 3 looks at the regional heterogeneity of this result. I find that high history is associated with higher insurance payout across the US regions. Notice that the Mid-Atlantic and South Atlantic region have higher than national average payouts but even there low surprise communities receive higher amounts. It is possible that low surprise events generate more insurance payouts because they experience more damaging events. Column (3) accommodates this by controlling for overall damage. 1% increase in total damage leads to 0.43% increase in insurance payouts at communities with low history of flooding and 0.66% increase in payouts at high flood history locations. Communities with previous floods 50% more of the damage through insurance compared to the rest. Column (4) shows that this result is consistent across regions of the US. Interestingly, the Mid-Atlantic area covers a bigger proportion of the overall damages with insurance but history of flooding still drives higher payouts. Columns (5) and (6) show that affected low-surprise locations have more active insurance policies and that the payout results are not driven by higher real estate values.

Overall, the results provide further confirmation of the group differences observed in the summary statistics. Locations with a history of flooding anticipate future damage and take out more insurance. The results also suggest that high damages in general do not necessarily lead to high impact on the local economy, outside rebuilding activities, because those may be in line with expectations and do not change the perceived risk.

Population Responses

Next I examine how the population is affected by flood events focusing on surprises and the level of attractiveness prior to the event. I estimate the following model in several variations:

$$\ln Pop_{ist} = \alpha_i + t_i + \gamma_{st} + \beta_1 F_{it-1} + \beta_2 PostF_{it-2} + \beta_3 PostTrend_{it-2} + \delta X_{it-1} + \{MFl_{it-1}\} + \epsilon_{ist} \quad (2)$$

Log population for community i within state s in year t is explained by an individual average, α_i, individual linear trend, t_i, and a state-year effect, γ_{st}. This specification is flexible enough to allow for time-invariant difference in settlement size and community-specific difference in the population trajectory. The former is important given the heterogeneity in community size in the data. The latter accounts for differences in productivity, amenities, and prior flood events which give rise to different population changes across locations. The state-year effect captures variations in local population which can be traced to the state/national level. The Great Recession is an important factor in the sample which has affected population and can be accommodated with the state-year controls.

I identify the effect of floods by first separating communities according to the number of floods. For the case of the single-flood group, I include an indicator for the year after the flood, F_{it-1} , an indicator for the period from the second year onwards, $PostF_{it-2}$, and a trend break after the flood, $PostTrend_{it-2}$. For the case of more than one floods I additionally include an indicator for the period(s) between the floods. The results in this paper focus on the single-hit communities since they represent the bulk of the location count and the identification is more straightforward. The β_1 represents the contemporaneous effect of the flood i.e. within the first year; β_2 captures the persistence of the initial effect; β_3 allows for a change in the trend relative to the pre-flood one. X_{it-1} includes a set of additional important indicators that have been interacted with F_{it-1}, $PostF_{it-2}$, and $PostTrend_{it-2}$. These include indicators for: top 66th percentile of FEMA/NFIP/SBA business/SBA homeowners damage shares; bottom 33th percentile of relative damages; top 50th percentile of share of non-construction occupations; top 50th percentile of share of renters. The last two indicators are based on the 2000 Census values and therefore are time-invariant. While the fixed effects already control for these differences I can still identify whether locations with more non-construction workers and more renters respond differently to flood events. The first controls for two separate effects: availability of job opportunities outside construction, which is usually over-represented in communities with less robust local economy; and the general lack of construction workers, which can lead to the inflow of such workers in order to conduct local repairs. The second controls for capacity to accommodate the displaced from floods, as well as emergency or temporary workers. Both can lead to increases in local population even if the community is hit by a flood. This control will not be sufficient if these additional workers are placed in temporary housing. In this case it is important to examine the persistence of the estimated flood impact since temporary workers will lead to a reversal of the initial impact as they leave.

The baseline results assume that the level of flood surprise does not affect the responses. I examine whether these differ by the level of surprise. Finally, I separate the impact by pre-flood population growth (last five years). Most communities have turnover in local population. Growing locations attract more new comers and experience demand for new housing because of improved labor market or/and local amenities. Conditioning on pre-growth can reveal how persistent demand for housing affects the overall response to a flood surprise. It also helps us interpret the trend break by identifying whether growing or stagnant locations see a change in trajectory. Note that pre-growth is time varying while the controls for the local economy/renters are not. The former accounts for higher-frequency shocks while the latter identifies lower-frequency ones such as whether the location is a bigger city. For example, places with diversified local economies are not expected to necessarily be growing. For that to happen they need additionally to be affected by a productivity shock. Although both factors are important I focus on the effect of the higher-frequency shock and simply control for the other one.

I also estimate the above model assuming that high-surprise location must have no lost buildings between 1978 and 2003. This limits the number of high-surprise communities but ensures that a flood event breaks with the location's history. Evidence from this specification can further confirm that results are driven by changes in expected flood risk.

Table 4 shows the results from the population model. Each of the three versions of the baseline model includes estimates without/with X_{it-1} controls. Population at the average location with flood from model (1) is not impacted by the event. The average location from model (2) with less diversified economy and lower availability of rentals among other controls sees a 0.92% decline in population in the year following the event. This decline is persistent and is accompanied by a decline in the pre-flood trajectory of 0.4%. The difference in results comes from the fact that the composition of the local economy, the availability of rentals, and the share of FEMA-recoded damages each soften the flood impact or in some cases increase population. While these are important results on their own the paper focuses on the impact of flood surprises and persistent demand for new housing so they are designated to the set of controls. Overall, model (2) shows that flooded places with lower rental share, higher construction occupations share, and intermediate damage shares see a decrease in expected population which is persistent and accompanied by a trend break. Even without accounting for the level of surprise population is negatively impacted.

The effect of flood surprises is identified in model (3) and (4). In both cases they lead to significant declines in population on impact and in the following periods. An average location from (3) is only affected when the flood is unexpected. On impact expected population drop by 0.3%; the effect is persistent; pre-flood trend declines by 0.15% after the event. Compared to (1) where floods do not affect population we see that identifying surprises is critical. This is consistent with the insurance results and suggests that revisions of flood risk disrupt the pre-flood population dynamic. In the case with controls flood surprises generate significantly bigger declines in population: 1.2% decline on impact, 1% in the post period, and 0.6% decline in pre trend. Low surprise floods also affect population. Interestingly, the regional results show that this effect is not a nation-wide phenomenon but comes from the northeastern region. Both estimates (3) and (4) strongly suggest that expected population declines when a flood occurrence breaks with historical experience. While the initial decline in population is persistent it is still relatively small at 1%. The trend break represents a much bigger impact on the population of a community following the event. A 0.6% decline in the pre-trend amounts to a 3%/6% lower population in 5/10 years relative to where population is expected to be without the flood. The fact that most events have relatively small magnitude implies that the effect stems from revisions of risk expectations. Consequently, biggest population changes will not necessarily overlap with biggest damages. Flooding seems to lead to some population increases in places with more diversified local economies and more rental capacity. This offsets the negative effect from the increase in riskiness. In the cases of flood surprises the second effect is much stronger and leads to overall decrease in population.

The evidence so far shows that surprises disrupt the pre-existing population trajectory. A decline in the linear trend implies a slow down in expansion and stabilizing of population in a growing location; in a stable or declining place it implies loss of population or an acceleration of such loss. To help interpret the trend break I separate the impact effects according to pre-flood growth: positive and negative growth in the preceding five years. This also helps understand how a productivity/amenity shock interacts with risk revisions. The results in (5) and (6) show that the surprise driven population decline occurs primarily in attractive communities with higher pre-flood growth. Population drops by 0.55%/1.4% without/with controls and remains lower in the post period. There is a decline in the pre trend of 0.4%/0.8%. These communities effectively stop expanding after the flood surprise and population becomes fixed at its pre-flood level. Locations with declining population are either not affected (with controls) or see an increase (without controls). The difference in outcomes by pre-growth after the surprise strongly suggests that the population decline works through the demand for new housing or excess of newcomers. This is consistent with a decrease in the attractiveness of the community following a revision of expected flood risk. Importantly, it requires that the real estate market does not fully compensate the risk increase with a discount that offsets the cost of insurance. Similarly, the fact that lower growth communities are not affected suggests that the real estate there may be discounted providing compensation for higher risk.

Results in (7) and (8) show that a stricter definition of flood surprise is associated with stronger declines in population. They imply that some of the locations with positive historical destruction likely anticipate future flooding. Yet, given that the estimated coefficients are similar this is not a big concern. Finally, Table A1 in the online appendix shows that the results are not changed when I increase the cut-off for a flood event to 0.02%, which is the 25^{th} percentile of the baseline sample as seen in the summary statistics. The results are also not affected when I drop locations with more than 8.66% of damage, which is the the 95^{th} percentile of the baseline sample for locations with multiple flood events. These results are listed in Table A2 in the online appendix.

It is important to point out an issue that relates to the possible endogeneity of flooding and local economic factors such as high poverty. It is possible that poor communities invest less in flood protection and ultimately experience bigger damages. Here it really matters how poverty or a local economic factor is related to the population trajectory before the flood and after the flood. If either of these cause population to be decreasing before the flood then I incorporate this in the model by allowing the trajectory to be different before the flood. For an impact to be significant in this case we have to see that population declines even more than suggested by pre-flood rates driven by poverty or an economic factor. If these factors cause population to respond differently only after the flood i.e. a poor place grows just as rich place before the flood then it is hard for me to disentangle the effect. I can only do it by allowing poor places to respond in a different way after the shock. I accommodate this possibility with a set of controls described above.

Real Estate Responses

I examine how the housing market responds to surprises and more specifically whether there is evidence of compensating effects by estimating the most restricted version of the model as in (6) above. Results are listed in Table 5 for each of the three tiers provided by Zillow.

There is no evidence that house values, across all three tiers, compensate for the increase in flood risk at locations with high pre-growth. The result is at odds with the observed decrease in population in the previous part, since a decline in house demand should lead to lower prices, holding house supply constant. To understand this, recall that the attractive communities are growing prior to the flood – growth achieved by new construction. The model by Capozza and Helsley (1990) shows that in the case of expanding communities higher risk leads to increases in the price and delays of new construction. It suggests that the increase in flood risk generates a decrease in the supply of new houses. The fact that equilibrium house prices do not adjust indicates that the community experiences both a decrease in the demand and supply of new houses. Alternatively, growing communities are likely to have an incentive to invest in home improvement after expected future risk increases. This is due to the higher price-to-cost ratio in these communities (Gyourko and Saiz 2004). In other words, following risk increases, owners can raises their homes and add another floor, among other improvements, which increases the house value. In either case, local housing becomes relatively more expensive and new-comers are steered to other locations, which limits the size of the community.

Interestingly, house prices in low-growth communities decline after a surprise. Top and middle-tier housing decrease by 2.3%-3.4% on impact; the dip is persistent and remains at close to 4.4% in the post period. Bottom-tier housing does not appear to decrease on impact although there is evidence of a decline in the post period. The change in real estate prices paired with the lack of population declines suggests that locations without demand for additional housing provide a discount that can compensate for the increase in expected flood risk and the associated costs. This result is similar to Glaeser and Gyourko (2005), and more recently to Notowidigdo (2011), who point out that negative productivity shocks will not lead to population declines but to reduction in local house prices.

All together the housing and population results suggest the following interpretation. Flood surprises drive upward revisions of the underlying probability of a future flood which in turn raises the cost of living. In locations where demand for housing is low, existing structures are sold at a discount that covers the additional cost. This appears to be sufficient to maintain the existing population trajectory. In location where demand for housing is high, there is both a decrease in the demand and supply of new housing. This leads house prices unchanged and reduces long-term population.

Low wealth incidence

The decline in house prices is consistent with turnover in the community whereby higher-risk tolerant households replace less-risk tolerant ones after a reduction in prices. This leaves population unchanged but alters the type of people remaining. This is an example of sorting based on changes in perceived risk. It relies on the assumption that households can finance their exit from the community by trading their house for a comparable structure somewhere else. If this is not the case sorting will not take place as people are prevented from leaving. This is an example of a lock-in effect as in Stein (1995).

I examine the extent to which low wealth can explain the lack of population changes in low growth areas. I do this by using the FEMA relief payments data. Guidelines from the agency imply that lower income applicants for disaster relief will be given non-refundable payments as opposed to loans. A lower-wealth household will be able to pay lower amount out of pocket and therefore will likely be given a higher non-refundable payment for a given amount of damage. I test whether flood incidence among low-wealth households is higher in low growth communities by examining total FEMA payments per damage recorded and how they differ in low-growth communities. In particular I estimate:

$$\ln(FemaPay)_i = \beta Dam_i + \gamma_1 Dam_i \times LSurp_i + \gamma_2 Dam_i \times LGr_i + \alpha_Y + \{MulFl\} + \epsilon_i \qquad (3)$$

where FemaPay is total relief payments per capita, Dam is total damages recorded, and α_Y is a year effect. The specification estimates the fraction of damages disbursed by fema, β, and allows this to be different for low-surprise events, γ_1, and at low growth locations, γ_2. Positive γ_2 indicates that FEMA disburses more per given amount of damages in low growth locations, a result consistent with higher low-wealth incidence of flooding.

Results are shown in Table 6. The national cross-section, (1), reveals that low-growth locations do receive more non-refundable payments per recorded damage. When I estimate the same model allowing for regional heterogeneity we see that floods affect poorer communities in low growth areas mostly in Northeast and Mid/South Atlantic. Overall, there is evidence that at least in some parts of the US insufficient wealth can explain the lack of population change after flood surprises. It suggests that sorting will not necessarily occur in these parts. It still remains to be seen how real estate values respond in those regions as well.

Let us go back to the case of Milford vs the two neighbors. Figure 4 shows the evolution of population and real estate. Milford has a high history of flooding and the flood events do not constitute surprises. We see that population and real estate values (top tier) are not affected. New Haven and Bridgeport, on the other hand, see a decline in population but in line with the results in this section housing closely follows the trajectory of Milford and does not decline. This puts the two neighbors in the high-pre-growth group where demand for new housing seems to prevent a compensating decline that offsets higher risk. The cost increase is consistent with population decline.

4 Regional Results

The main results are based on a national sample which combines locations across various geographies each with specific climates and regulatory settings. The econometric specification accounts for this heterogeneity with the individual average, trend, and state-year effects but we cannot be certain that the identified responses are a general phenomenon occurring across the country. It is possible that population responds strongly only in one area of the US with there being no effect elsewhere. Additionally, I have also argued that real estate variations are closely related and help understand population effects. It is important to confirm that this relationship is maintained within separate regions. I investigate within-country heterogeneity by allowing the main coefficients to vary by a grouping based on a mix between Census divisions and regions – region 1 is split into Northeast and Mid-Atlantic; region 3 is split into South Atlantic and South Central.

The regional results for population are listed in Table 7. The table includes coefficients from one estimation – different columns show estimates by surprise/pre-growth group. For example, the coefficients for the high-surprise/high-growth group from the Mid-Atlantic region is listed in the second column rows 2, 8, and 14. The results confirm that surprises affect population at high pre-growth communities. Not all regions experience on impact, post, and trend break effects but all of them feature some combination. This suggests that the national results identify a general phenomenon where new movers choose a different destination after risk increases. Notice that the population decline at high pre-growth communities with low surprises estimated in the main results actually can be traced exclusively to the Northeast region and is not as general. This cautions against directly interpreting the national results without confirming that they hold at the regional level.

Regional real estate results for top-tier housing are shown in Table 8. We see no real estate depreciation in any of the regions for high-surprise/high-growth locations. The only exception is the Northeast region which sees a trend break. This supports the interpretation of the population declines. The case of the South Atlantic is somewhat different. High-surprise/high-growth areas do not experience population decline on impact – they see a trend break. This implies that population was not significantly affected and demand for new housing persisted. Uninterrupted population is reflected in the increase in house prices for this group. This suggests that expected flood risk may not have adjusted significantly after the flood surprises. Alternatively, it is likely that the high-surprise group includes locations where risk is already perceived to be high – consistent with the insurance estimates for South Atlantic in Table 3.

Housing depreciates in low pre-growth communities in all regions except for the Midwest and South Central. The price reduction paired with minimal changes in population in these locations is consistent with turnover in the local population where some sorting based on risk occurs. In the case of Midwest and South Central there are both minimal population changes and no price adjustment. Living in these areas effectively becomes more expensive but the real estate does not provide compensation. The evidence from the FEMA payments suggests that at least for the South Central area the incidence of the disaster may be higher on low-wealth households. This can explain why we do not observe any population effects – these communities are locked in.

Overall, the regional results for housing and population are closely matched. They provide evidence for the interaction between revisions of perceived flood risk and existing demand for new housing which ultimately determine whether more people will inhabit risky locations.

5 Extensions and Robustness

Flood Spillovers

The results in the paper shed light on the effect that floods have on other locations that may not themselves be affected. To accommodate this I extend the baseline model in two important ways: add a set of indicators in X_{it} that allow the impact, persistence, and trend-break effects to differ for locations next to counties with floods; estimate a set of flood effects for locations that do not experience a flood but are located in a county where others have floods. The first case makes sure that the baseline results are not driven by events in neighboring counties i.e. that being next to a multiple-flood county drives population away not the flood at location. The second case looks at the possible change in perceived risk that occurs in places that are close to floods. Gallagher (2014) shows that insurance purchases pick up after floods in locations in the same media market. Here I explore whether there are additional population and real estate values effects.

The evidence is shown in Table 9. Model (1) estimates the baseline results with the addition of controls for floods occurring in the neighboring counties. We see that the results are robust to this set of controls. In Model (2) shows that locations that are not affected directly but are within an affected county experience a decline in population and a trend break. This is consistent with an increase in perceived risk and further supports the point that the impact of floods events works mainly thought change in expectations. Model (3) separates the previous effect depending on whether the nearby floods were surprises. The results are mixed suggesting that proximity to high surprises being marginally significant. It is not obvious a-priori if low or high surprise floods will have different spillover effects. The evidence suggests that low-surprise floods have stronger population effects. Models (4)-(6) examine the effect on real estate values. We see negative spillovers on top- and mid-tier housing. The spillover of a high-surprise flood has a stronger effect on prices which is consistent with the weaker population impact.

Relative Damage vs Flood Indicator

The results in this paper use an indicator for a flood based on a cutoff for minimum relative damage. I investigate the extent to which actual relative damage affects the main results regarding population. I introduce variations in damage by replacing the flood indicator with three indicators for relative damage. These indicators reflect the lower 33^{th}/33^{th}-66^{th}/upper

66^{th} percentile respectively of the distribution of damages at the state level. Specifying the main population model with them rather than a flood indicator allows us to examine whether events with relatively higher damage are different from those with relatively lower one. The results are shown in Table 10. Focusing on the models with controls we can see that all parts of the damage distribution reduce population for the respective groups that are affected in the main results. The effect of the upper 66^{th} percentile is slightly lower while the lower 33^{th} percentile generally has higher effects. These are not statistically different from each other.

Local Social Organizations and Churches

A big literature on resilience after natural disasters emphasizes the importance of local social capital (Aldrich 2012). Literature on deeper roots of productivity across the US also emphasizes endowments of social capital (Fulford et al 2018). To accommodate this I use information from the County Business Patterns dataset which lists the total number of establishments at a zip code by 6-digit industry code. I calculate the total number of civic and social organizations (NAICS 813410) and religious organizations (NAICS 813110) per capita in each community and define an indicator for locations with above state-median number. I then include it among the rest of the controls in X_{it}. The results for population and real estate are listed in Table 11. The coefficient estimates for the impact of higher level of social capital are listed at the bottom of the table. The overall results are very similar to the baseline. Social capital weakens the decline in the pre-flood trend for population and lowers the decline in the post period for the real estate values. These results are consistent with the literature on social capital which suggests that communities with higher endowment will do better after disasters.

6 Conclusion

This is the first study that investigates the effect of flood surprises using consistent national data of insured and uninsured damages at the level of the community. It investigates how changes in underlying flood risk affect the local population trajectory and real estate values. I find that changes in risk expectations are much more important that the amount of overall damage – at least in the case of lower scale events. Locations with a history of flooding do not experience changes in population and real estate. This indicates that flooding is widely expected and the local population is already somewhat insulated from the risk with insurance. Locations with flood surprises see a combination of declines in population and house value depreciation. The level of pre-existing demand for new housing is critical. Attractive communities that are surprised by a flood experience population declines and no housing depreciation, a combination consistent with new comers steering away. Less attractive locations see predominately house price declines and stable population. Using these results to interpret how climate change will affect communities within the US we will see three general local outcome. First, risky locations will not see any changes. Second, attractive locations where risk increases will experience population declines leading to stabilizing of population at the pre-flood level. Third, locations where risk increase and where demand for new housing is low will not see changes in population but will experience depreciation of housing.

Tables and Figures

Table 1: Summary Statistics by Number of Floods

Floods	Freq.	Percent	Cum.
0	1,771	42.71	42.71
1	1,519	36.63	79.33
2	542	13.07	92.4
3	238	5.74	98.14
4	77	1.86	100
Total	4,147	100	

Relative Damage

Fl	p25	p50	p75	p90	p95
1	0.02%	0.05%	0.14%	0.46%	0.87%
2	0.02%	0.06%	0.19%	0.69%	1.55%
3	0.02%	0.07%	0.25%	0.86%	1.72%
4	0.02%	0.09%	0.34%	1.27%	8.66%

Total Damage

Fl	p25	p50	p75	p90	p95
1	0.64	1.67	5.02	16.14	42.39
2	0.64	1.80	5.70	20.75	47.18
3	0.79	2.45	9.14	33.90	76.74
4	0.83	3.42	13.50	69.68	213.80

Average Pop (1,000)

Fl	p25	p50	p75	p90	p95
0	21	34	62	111	167
1	21	31	57	110	179
2	22	32	55	104	207
3	21	35	60	139	214
4	23	36	77	138	184

Population Growth

Fl	p25	p50	p75	p90	p95
0	-0.04%	0.55%	1.36%	2.50%	3.44%
1	-0.15%	0.39%	1.14%	2.22%	3.18%
2	-0.24%	0.28%	0.97%	1.97%	2.90%
3	-0.27%	0.21%	0.75%	1.71%	2.51%
4	-0.20%	0.31%	0.96%	2.20%	3.12%

	Number of Floods			
State	0	1	2	3+
Alabama	41	50	5	
Arkansas	20	40	17	
California	316	45	1	
Colorado	38	23		
Connecticut	36	33	7	5
Delaware	4	2		
Florida	7	99	34	47
Georgia	99	43	12	3
Illinois	74	74	54	27
Indiana	38	88	6	4
Iowa	6	44	29	
Kentucky	22	48	31	6
Louisiana	6	6	20	40
Maryland	29	5		
Massachusetts	46	67	21	2
Minnesota	90	23	6	2
Mississippi	8	30	26	23
Missouri	38	48	30	
Nevada	13	2		
New Hampshire	2	24		
New Jersey	12	83	14	77
New York	66	74	19	34
North Carolina	82	51	8	2
North Dakota		4	11	
Ohio	89	73	34	6
Oklahoma	25	38	15	
Oregon	45	10	2	
Pennsylvania	39	82	49	31
Rhode Island	2	12	14	
South Carolina	51	15		
South Dakota	7	7	1	
Tennessee	38	75		
Texas	170	65	56	
Vermont	3	13	2	
Virginia	67	28	6	4
Washington	64	26		
West Virginia	20	23	5	2
Wisconsin	58	46	7	
Total	1771	1519	542	315

Table 2: Summary Statistics by Surprise and Pre-Flood Growth

		Single Flood			Single Flood				
	No		Surprise		High Surprise		Low Surprise		Two+
	Flood	All	High	Low	Low Growth	High Growth	Low Growth	High Growth	Floods
Count	1771	1519	934	585	229	705	171	414	857
Relative Damage	0	0.05%	0.04%	0.07%	0.05%	0.04%	0.08%	0.06%	0.06%
Total $ Damage (100k)	0	16.67	13.43	24.51	12.91	13.55	18.49	27.36	21.04
Share of Insured Damages	0	14.42%	7.45%	24.83%	3.50%	9.39%	24.57%	25.21%	27.82%
Share of Uninsured FEMA	0	17.44%	20.65%	13.66%	23.67%	19.50%	11.83%	14.29%	13.80%
Share of Uninsured Home SBA	0	2.78%	2.74%	2.87%	4.08%	2.38%	2.04%	3.19%	1.69%
Share of Uninsured Business SBA	0	22.42%	24.77%	19.75%	23.91%	25.48%	16.16%	20.49%	19.42%
Total Structures Lost (1978/2000)	0	0.27%	0.12%	0.83%	0.13%	0.12%	0.93%	0.81%	0.89%
Population (10k)	33.66	31.35	30.38	33.67	25.53	32.84	26.25	38.97	32.73
Median Income (10k)	39.89	38.78	38.23	39.22	33.49	40.56	35.16	41.14	37.54
Population Growth	0.55%	0.39%	0.41%	0.35%	-0.31%	0.70%	-0.30%	0.65%	0.26%
Fraction of Population in 100 year zone	0.00%	0.08%	0.03%	0.77%	0.00%	0.07%	0.04%	1.51%	1.93%
Insurance Policies	67	120	72	261	54	80	234	271	256
Total $ Coverage (1M)	10.65	15.92	10.48	32.51	7.37	11.76	25.99	35.76	32.54
Top Tier House Value	2.19	1.90	1.88	1.92	1.17	2.12	1.28	2.22	1.80
Middle Tier House Value	1.45	1.25	1.24	1.26	0.73	1.39	0.82	1.44	1.19
Bottom Tier House Value	1.00	0.84	0.83	0.85	0.46	0.93	0.50	1.01	0.77

Table lists median values for the listed variables.

Table 3: Flood Surprises and Insurance

VARIABLES	(1) $\ln(Payouts)_i$	(2) $\ln(Payouts)_i$	(3) $\ln(Payouts)_i$	(4) $\ln(Payouts)_i$	(5) $\ln(Policies)_i$	(6) $\ln(Policies)_i$
F	0.450*					
	(0.230)					
F × LSurprise	0.963***					
	(0.119)					
F × Northeast		0.0442				
		(0.588)				
F × Mid-Atlantic		0.706***				
		(0.228)				
F × Midwest		-0.0915				
		(0.216)				
F × South Atlantic		1.048**				
		(0.472)				
F × South Central		0.209				
		(0.358)				
F × West		-0.438				
		(0.307)				
F × Northeast × LSurp		1.338***				
		(0.145)				
F × Mid-Atlantic × LSurp		0.929***				
		(0.150)				
F × Mid West × LSurp		1.265***				
		(0.257)				
F × South Atlantic × LowSurp		0.624*				
		(0.339)				
F × South Central × LSurp		0.796***				
		(0.221)				
F × West × LSurp		1.668***				
		(0.185)				
F × Dam			0.428***		0.841***	
			(0.0886)		(0.0978)	
F × Dam × LSurprise			0.234***		0.266***	
			(0.0276)		(0.0370)	
F × Dam × Northeast				0.476***		0.537***
				(0.148)		(0.0844)
F × Dam × Mid-Atlantic				0.640***		0.979***
				(0.0508)		(0.0919)
F × Dam × Midwest				0.396***		0.420**
				(0.0554)		(0.170)
F × Dam × South Atlantic				0.355***		1.045***
				(0.115)		(0.0730)
F × Dam × South Central				0.448***		0.447***
				(0.0840)		(0.0899)
F × Dam × West				0.366***		0.916***
				(0.0597)		(0.0845)
F × Dam × Northeast × LSurp				0.266***		0.310***
				(0.0593)		(0.0420)
F × Dam × Mid-Atlantic × LSurp				0.153***		0.176***
				(0.00957)		(0.0465)
F × Dam × Mid West × LSurp				0.298***		0.467***
				(0.0227)		(0.0571)
F × Dam × South Atlantic × LowSurp				0.241***		0.290***
				(0.0428)		(0.0439)
F × Dam × South Central × LSurp				0.171***		0.321**
				(0.0594)		(0.115)
F × Dam × West × LSurp				0.317***		0.247**
				(0.0438)		(0.0915)
Observations	3,443	3,443	3,443	3,443	1,474	1,474
R-squared	0.613	0.620	0.778	0.793	0.867	0.891
X_{it} Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. $\ln(Payouts)_i$ is log insurance payouts per capita at location i. $\ln(Policies)_i$ is log of active insurance policies. F is an indicator for flooding at a single-flood location. Dam is total damage per capita. $LSurp$ is an indicator for a high history of flooding i.e. low-surprise event. The estimation results do not report the coefficients for multiple-flood communities. Sample covers the period between 2000 and 2016. SE clustered by state.

Table 4: Flood Surprises and Population Changes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			HSurp: Below State Median Lost Structures				HSurp: No Lost Structures	
VARIABLES	ln Pop_{ist}	ln Pop_{ist}	ln Pop_{ist}	ln Pop_{ist}	ln Pop_{ist}	ln Pop_{ist}	ln Pop_{ist}	ln Pop_{ist}
F	-0.000840	-0.00918***						
	(0.00113)	(0.00203)						
PostF	-0.00396***	-0.00934***						
	(0.00144)	(0.00278)						
PostTrend	-4.08e-05	-0.00404***						
	(0.000484)	(0.000855)						
F × HSurp			-0.00310**	-0.0120***			-0.0173**	
			(0.00121)	(0.00241)			(0.00691)	
F × LSurp			0.00292	-0.00487**			-0.00889***	
			(0.00193)	(0.00234)			(0.00203)	
PostF × HSurp			-0.00462***	-0.0103***			-0.0162*	
			(0.00174)	(0.00312)			(0.00941)	
PostF × LSurp			-0.00259	-0.00758**			-0.00916***	
			(0.00217)	(0.00309)			(0.00282)	
PostTrend × HSurp			-0.00148**	-0.00582***			-0.00911***	
			(0.000582)	(0.000911)			(0.00322)	
PostTrend × LSurp			0.00213***	-0.00140			-0.00383***	
			(0.000615)	(0.000931)			(0.000848)	
F × HSurp × LGr					0.00664***	-0.00305		-0.00703
					(0.00115)	(0.00243)		(0.00454)
F × HSurp × HGr					-0.00552***	-0.0141***		-0.0197**
					(0.00142)	(0.00243)		(0.00879)
F × LSurp × LGr					0.0118**	0.00347		0.000248
					(0.00537)	(0.00505)		(0.00257)
F × LSurp × HGr					0.000115	-0.00752***		-0.0113***
					(0.00132)	(0.00210)		(0.00212)
PostF × HSurp× LGr					0.000943	-0.00530		-0.0107*
					(0.00190)	(0.00333)		(0.00625)
PostF × HSurp× HGr					-0.00534***	-0.0113***		-0.0155
					(0.00206)	(0.00315)		(0.0122)
PostF × LSurp× LGr					0.00253	-0.00267		-0.00390
					(0.00478)	(0.00474)		(0.00310)
PostF × LSurp× HGr					-0.00329	-0.00841***		-0.00999***
					(0.00213)	(0.00318)		(0.00289)
PostTrend × HSurp× LGr					0.00695***	0.00222**		0.000915
					(0.000597)	(0.000894)		(0.00213)
PostTrend × HSurp× HGr					-0.00410***	-0.00788***		-0.0130***
					(0.000655)	(0.000917)		(0.00422)
PostTrend × LSurp× LGr					0.00891***	0.00498***		0.00360***
					(0.000874)	(0.00104)		(0.000842)
PostTrend × LSurp× HGr					-0.000591	-0.00381***		-0.00609***
					(0.000693)	(0.000967)		(0.000835)
Observations	70,403	70,403	70,403	70,403	70,403	70,403	70,403	70,403
Within R-squared	0.005	0.023	0.009	0.028	0.039	0.052	0.025	0.05
X_{it} Controls	No	Yes	No	Yes	No	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1.F is an indicator for flood event. PostF is an indicator for the period following the first year of impact. PostTrend is a linear trend starting the in the period following the impact. LSurp/HSurp is an indicator for a low/high surprise event. LGr/HGr is an indicator for positive/negative population growth 5 years prior to the event. Estimation (7) and (8) use a different definition for surprise – zero buildings destroyed between 1978 and 2003. Sample: 2000/2016. SE clustered by community. Additional controls: indicators for top 66^{th} perc. of fema/insured/business/sba damage; above median non-construction-based local economy; above median renter fraction; below 33^{th} perc. tot. damage. The estimation results do not report the coefficients for multiple-flood communities.

Table 5: Flood Surprises and Real Estate Values

VARIABLES	(1) TopTier	(2) MiddleTier	(3) BottomTier
F × HSurp × LGr	-0.0338***	-0.0230*	-0.0204
	(0.0122)	(0.0134)	(0.0162)
F × HSurp × HGr	-0.00211	0.00941	0.0175
	(0.00900)	(0.00916)	(0.0117)
F × LSurp × LGr	-0.0147	0.00534	0.00815
	(0.0138)	(0.0129)	(0.0167)
F × LSurp × HGr	0.00410	0.0132	0.0170
	(0.00944)	(0.00943)	(0.0120)
PostF × HSurp× LGr	-0.0425***	-0.0439**	-0.0553***
	(0.0153)	(0.0174)	(0.0204)
PostF × HSurp× HGr	-0.00408	0.00425	0.00116
	(0.0115)	(0.0115)	(0.0142)
PostF × LSurp× LGr	-0.0117	0.00724	-0.0166
	(0.0176)	(0.0173)	(0.0200)
PostF × LSurp× HGr	-0.000138	-0.00135	-0.00581
	(0.0123)	(0.0123)	(0.0149)
PostTrend × HSurp× LGr	-0.000319	0.00314	0.00870*
	(0.00365)	(0.00403)	(0.00471)
PostTrend × HSurp× HGr	-0.00526*	-0.00270	0.000444
	(0.00278)	(0.00296)	(0.00331)
PostTrend × LSurp× LGr	-0.00615	-0.00567	0.00167
	(0.00402)	(0.00416)	(0.00450)
PostTrend × LSurp× HGr	-0.00588**	-0.00341	0.000448
	(0.00290)	(0.00297)	(0.00362)
Observations	61,454	60,825	54,459
Within R-squared	0.02	0.023	0.021
X_{it} Controls	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Top/Middle/BottomTier refers to the log of the respective house price Zillow index. F is an indicator for flood event. PostF is an indicator for the period following the first year of impact. PostTrend is a linear trend starting the in the period following the impact. LSurp/HSurp is an indicator for a low/high surprise event. LGr/HGr is an indicator for positive/negative population growth 5 years prior to the event. Sample: 2000/2016. SE clustered by community. Additional controls: indicators for top 66^{th} perc. of fema/insured/business/sba damage; above median non-construction-based local economy; above median renter fraction; below 33^{th} perc. tot. damage.

Table 6: Low-wealth Incidence in Low-Growth Communities

VARIABLES	(1) ln($FemaPay$)	(2) ln($FemaPay$)
F × Dam	0.859***	
	(0.0141)	
F × Dam × LSurp	-0.00489	
	(0.00808)	
F × Dam × LGr	0.0307**	
	(0.0143)	
F × Dam × Northeast		0.923***
		(0.0285)
F × Dam × Mid-Atlantic		0.816***
		(0.0188)
F × Dam × Midwest		0.911***
		(0.0154)
F × Dam × South Atlantic		0.816***
		(0.0162)
F × Dam × South Central		0.881***
		(0.0102)
F × Dam × West		0.821***
		(0.0247)
F × Dam × LSurp × Northeast		-0.0435
		(0.0392)
F × Dam × LSurp × Mid-Atlantic		0.0140
		(0.0244)
F × Dam × LSurp × Midwest		-0.0116
		(0.0143)
F × Dam × LSurp × South Atlantic		0.00162
		(0.0143)
F × Dam × LSurp × South Central		-0.0158
		(0.0130)
F × Dam × LSurp × West		-0.0159
		(0.0243)
F × Dam × LGr × Northeast		0.0318**
		(0.0124)
F × Dam × LGr × Mid-Atlantic		0.0253***
		(0.00757)
F × Dam × LGr × Midwest		0.00139
		(0.0190)
F × Dam × LGr × South Atlantic		-0.00168
		(0.0267)
F × Dam × LGr × South Central		0.0359*
		(0.0191)
F × Dam × LGr × West		-0.109**
		(0.0521)
Observations	3,105	3,145
R-squared	0.973	0.971
X_{it} Controls	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. FemaPay refers to total FEMA relief per capita, Dam refers to total FEMA damage recorded, LSurp is an indicator for low-surprise event, and LGr is an indicator for low pre-growth location. Sample: 2000/2016. SE clustered by state. Additional controls: indicators for top 66^{th} perc. of fema/insured/business/sba damage; above median non-construction-based local economy; above median renter fraction; below 33^{th} perc. tot. damage.

Table 7: Regional Population Responses

	$\ln Pop^{st}_{ist}$			
	HighSurprise		*LowSurprise*	
VARIABLES	*LowGrowth*	*HighGrowth*	*LowGrowth*	*HighGrowth*
F × Northeast	-0.00754**	-0.0101***	-0.00669*	-0.00998***
	(0.00303)	(0.00286)	(0.00396)	(0.00273)
F × Mid-Atlantic	-0.00504	-0.0163***	0.00213	-0.00901*
	(0.00540)	(0.00488)	(0.00376)	(0.00463)
F × Midwest	0.00438	-0.0137***	-0.000326	-0.00311
	(0.00355)	(0.00381)	(0.00577)	(0.00295)
F × South Atlantic	0.000893	-0.00667	0.00518	-0.00812
	(0.00687)	(0.00576)	(0.00532)	(0.00507)
F × South Central	-0.00315	-0.0141**	0.0184	-0.00271
	(0.00668)	(0.00630)	(0.0164)	(0.00611)
F × West	-5.64e-05	-0.0189***	-0.00613	-0.00849
	(0.0104)	(0.00660)	(0.0123)	(0.00832)
PostF × Northeast	-0.0142***	-0.0175***	-0.0122*	-0.0139***
	(0.00527)	(0.00435)	(0.00676)	(0.00455)
PostF × Mid-Atlantic	-0.00925	-0.0113	-0.00333	-0.0113
	(0.00998)	(0.00786)	(0.00711)	(0.00765)
PostF × Midwest	0.000359	-0.0134***	-0.00254	0.000863
	(0.00434)	(0.00450)	(0.00531)	(0.00403)
PostF × South Atlantic	-0.00438	-0.00197	-0.00829	-0.0164**
	(0.00908)	(0.00794)	(0.00793)	(0.00800)
PostF × South Central	-0.00242	-0.00915	0.0113	0.00184
	(0.00815)	(0.00802)	(0.0143)	(0.00999)
PostF × West	0.00316	-0.0267***	-0.0112	-0.0132
	(0.0130)	(0.00820)	(0.0163)	(0.0105)
PostTrend × Northeast	0.00171	-0.000892	0.00366	-0.00297**
	(0.00154)	(0.00147)	(0.00230)	(0.00149)
PostTrend × Mid-Atlantic	0.00374	-0.00868***	0.00531**	-0.00171
	(0.00290)	(0.00268)	(0.00252)	(0.00256)
PostTrend × Midwest	0.00396***	-0.00714***	0.00443***	-0.00498***
	(0.00117)	(0.00157)	(0.00129)	(0.00133)
PostTrend × South Atlantic	0.000617	-0.0112***	0.00492*	-0.00305
	(0.00293)	(0.00249)	(0.00276)	(0.00250)
PostTrend × South Central	0.00477***	-0.00460***	0.00850***	-0.000660
	(0.00183)	(0.00176)	(0.00277)	(0.00263)
PostTrend × West	0.00638*	-0.0106***	0.00903**	-0.00701**
	(0.00362)	(0.00306)	(0.00446)	(0.00281)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Consult notes for Table 4 for details. Sample: 2000/2016. SE clustered by community. Additional controls: indicators for top 66^{th} perc. of fema/insured/business/sba damage; above median non-construction-based local economy; above median renter fraction; below 33^{th} perc. tot. damage.

Table 8: Regional Real Estate Responses for Top Tier Housing

	TopTier House Index			
	HighSurprise		*LowSurprise*	
VARIABLES	*LowGrowth*	*HighGrowth*	*LowGrowth*	*HighGrowth*
F × Northeast	-0.0404**	-0.0296*	-0.0280	-0.0381**
	(0.0191)	(0.0153)	(0.0256)	(0.0151)
F × Mid-Atlantic	0.00921	0.0203	0.0108	-0.00540
	(0.0293)	(0.0260)	(0.0332)	(0.0253)
F × Midwest	-0.0196	0.00228	0.00589	0.0163
	(0.0222)	(0.0157)	(0.0181)	(0.0148)
F × South Atlantic	-0.0917***	0.0378**	-0.0200	0.0232
	(0.0251)	(0.0164)	(0.0308)	(0.0175)
F × South Central	-0.00133	0.00963	0.0132	0.0459**
	(0.0228)	(0.0193)	(0.0245)	(0.0218)
F × West	-0.159***	-0.00704	-0.120***	-0.0419
	(0.0300)	(0.0274)	(0.0299)	(0.0282)
PostF × Northeast	-0.0572**	-0.0373*	-0.0356	-0.0519**
	(0.0268)	(0.0221)	(0.0355)	(0.0220)
PostF × Mid-Atlantic	-0.0959***	-0.0261	-0.0492	-0.0597*
	(0.0370)	(0.0333)	(0.0414)	(0.0323)
PostF × Midwest	0.000684	0.0177	0.0161	0.0361**
	(0.0256)	(0.0167)	(0.0234)	(0.0163)
PostF × South Atlantic	-0.0428	0.0459*	-0.000888	0.0241
	(0.0395)	(0.0253)	(0.0372)	(0.0295)
PostF × South Central	0.0134	0.0173	0.0339	0.0424
	(0.0296)	(0.0240)	(0.0359)	(0.0266)
PostF × West	-0.219***	-0.0265	-0.0863*	-0.0806**
	(0.0424)	(0.0330)	(0.0501)	(0.0387)
PostTrend × Northeast	-0.0154**	-0.0126**	-0.00827	-0.00917
	(0.00642)	(0.00568)	(0.00969)	(0.00604)
PostTrend × Mid-Atlantic	0.0287***	0.00497	0.0218**	0.0128
	(0.00967)	(0.00966)	(0.00913)	(0.00814)
PostTrend × Midwest	-0.00199	-0.00443	-0.00780	-0.00386
	(0.00522)	(0.00420)	(0.00493)	(0.00430)
PostTrend × South Atlantic	-0.0280***	-0.00343	-0.0201*	-0.0182**
	(0.0101)	(0.00815)	(0.0117)	(0.00780)
PostTrend × South Central	0.00462	-0.00172	-0.00222	0.00628
	(0.00758)	(0.00576)	(0.00760)	(0.00599)
PostTrend × West	-0.00554	-0.00358	0.00233	-0.0103
	(0.0107)	(0.00710)	(0.0266)	(0.00821)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Consult notes for Table 5. Sample: 2000/2016. SE clustered by community. Additional controls: indicators for top 66^{th} perc. of fema/insured/business/sba damage; above median non-construction-based local economy; above median renter fraction; below 33^{th} perc. tot. damage.

Table 9: Flood Spillovers

VARIABLES	(1) ln Pop_{ist}	(2) ln Pop_{ist}	(3) ln Pop_{ist}	(4) TopHVI	(5) MidHVI	(6) BotHVI
F × HSurp × LGr	-0.00283	-0.00326	-0.00321	-0.0348***	-0.0239*	-0.0231
	(0.00293)	(0.00295)	(0.00295)	(0.0129)	(0.0142)	(0.0176)
F × HSurp × HGr	-0.0140***	-0.0143***	-0.0143***	-0.00381	0.00761	0.0136
	(0.00288)	(0.00288)	(0.00288)	(0.00964)	(0.0100)	(0.0131)
F × LSurp × LGr	0.00409	0.00371	0.00371	-0.0156	0.00443	0.00556
	(0.00476)	(0.00477)	(0.00477)	(0.0144)	(0.0138)	(0.0181)
F × LSurp × HGr	-0.00685***	-0.00733***	-0.00734***	0.00403	0.0121	0.0143
	(0.00238)	(0.00239)	(0.00239)	(0.00989)	(0.0100)	(0.0127)
PostF × HSurp× LGr	-0.00668*	-0.00716*	-0.00708*	-0.0346**	-0.0327*	-0.0455**
	(0.00387)	(0.00390)	(0.00390)	(0.0159)	(0.0181)	(0.0220)
PostF × HSurp× HGr	-0.0134***	-0.0137***	-0.0137***	-0.000572	0.0106	0.00442
	(0.00368)	(0.00368)	(0.00368)	(0.0122)	(0.0124)	(0.0156)
PostF × LSurp× LGr	-0.00357	-0.00404	-0.00397	-0.00518	0.0184	-0.00556
	(0.00466)	(0.00467)	(0.00467)	(0.0180)	(0.0181)	(0.0212)
PostF × LSurp× HGr	-0.00887***	-0.00943***	-0.00938***	0.00617	0.00749	0.00155
	(0.00344)	(0.00345)	(0.00345)	(0.0131)	(0.0131)	(0.0159)
PostTrend × HSurp× LGr	0.00212**	0.00224**	0.00229**	-0.00338	-0.000543	0.00600
	(0.00103)	(0.00104)	(0.00104)	(0.00388)	(0.00421)	(0.00504)
PostTrend × HSurp× HGr	-0.00784***	-0.00764***	-0.00760***	-0.00696**	-0.00511	-0.000937
	(0.000961)	(0.000970)	(0.000969)	(0.00298)	(0.00312)	(0.00354)
PostTrend × LSurp× LGr	0.00491***	0.00509***	0.00513***	-0.00894**	-0.00928**	-0.00127
	(0.00111)	(0.00113)	(0.00113)	(0.00431)	(0.00437)	(0.00481)
PostTrend × LSurp× HGr	-0.00386***	-0.00367***	-0.00362***	-0.00795**	-0.00629**	-0.00191
	(0.00102)	(0.00103)	(0.00103)	(0.00314)	(0.00316)	(0.00373)
$\text{F}^{Neighbor}$		-0.00975**				
		(0.00427)				
$\text{PostF}^{Neighbor}$		-0.00469				
		(0.00545)				
$\text{PostTrend}^{Neighbor}$		-0.00375**				
		(0.00168)				
$\text{F}^{Neighbor}$ × HSurp			-0.00862*	-0.0301**	-0.0354***	-0.0195
			(0.00480)	(0.0143)	(0.0135)	(0.0165)
$\text{F}^{Neighbor}$ × LSurp			-0.00936**	-0.0250**	-0.0282***	-0.0176
			(0.00420)	(0.0103)	(0.0105)	(0.0122)
$\text{PostF}^{Neighbor}$ × HSurp			-0.00670	-0.0234	-0.0552***	-0.0525***
			(0.00602)	(0.0182)	(0.0158)	(0.0182)
$\text{PostF}^{Neighbor}$ × LSurp			-0.00115	-0.0370***	-0.0614***	-0.0657***
			(0.00570)	(0.0142)	(0.0144)	(0.0165)
$\text{PostTrend}^{Neighbor}$ × HSurp			-0.00593***	-0.00461	0.00138	0.00425
			(0.00180)	(0.00451)	(0.00398)	(0.00460)
$\text{PostTrend}^{Neighbor}$ × LSurp			-0.00201	-0.00477	-0.00328	0.000537
			(0.00183)	(0.00369)	(0.00357)	(0.00407)
Observations	69,927	69,927	69,927	61,378	60,844	54,497
Within R-squared	0.064	0.081	0.083	0.032	0.036	0.034
Neighbor County Flood Controls	Yes	Yes	Yes	Yes	Yes	Yes
X_{it} Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1.F is an indicator for flood event. PostF is an indicator for the period following the first year of impact. PostTrend is a linear trend starting the in the period following the impact. LSurp/HSurp is an indicator for a low/high surprise event. LGr/HGr is an indicator for positive/negative population growth 5 years prior to the event. $\text{F}^{Neighbor}$ is an indicator for a community with no flooding located in county with a single flood only. $\text{PostF}^{Neighbor}$ and $\text{PostTrend}^{Neighbor}$ are respectively the post- and post-trend for such a location. Sample: 2000/2016. SE clustered by community. Additional controls: indicators for top 66^{th} perc. of fema/insured/business/sba damage; above median non-construction-based local economy; above median renter fraction; below 33^{th} perc. tot. damage. The estimation results do not report the coefficients for multiple-flood communities.

Table 10: Population Responses with Spline Damage Specification

VARIABLES	(1) ln Pop_{ist}	(2) ln Pop_{ist}	(3) ln Pop_{ist}	(4) ln Pop_{ist}
F × Dam1	-0.000581	-0.00872***		
	(0.00181)	(0.00241)		
PostF × Dam1	-0.00343	-0.00833**		
	(0.00221)	(0.00342)		
PostTrend × Dam1	0.000144	-0.00371***		
	(0.000606)	(0.000927)		
F × Dam2	-0.00191	-0.00995***		
	(0.00162)	(0.00220)		
PostF × Dam2	-0.00455*	-0.00958***		
	(0.00238)	(0.00296)		
PostTrend × Dam2	-0.00104	-0.00473***		
	(0.000800)	(0.000931)		
F × Dam3	0.000262	-0.00760***		
	(0.00134)	(0.00229)		
PostF × Dam3	-0.00383*	-0.00861**		
	(0.00200)	(0.00343)		
PostTrend × Dam3	0.000915	-0.00277***		
	(0.000675)	(0.00102)		
F × HSurp × Dam1			-0.00441**	-0.0130***
			(0.00173)	(0.00327)
F × LSurp × Dam1			0.00823*	0.00108
			(0.00433)	(0.00360)
PostF × HSurp × Dam1			-0.00679***	-0.0143***
			(0.00249)	(0.00482)
PostF × LSurp × Dam1			0.00460	0.00313
			(0.00424)	(0.00420)
PostTrend × HSurp × Dam1			-0.00118	-0.00498***
			(0.000730)	(0.00126)
PostTrend × LSurp × Dam1			0.00292***	-0.000330
			(0.000887)	(0.00116)
F × HSurp × Dam2			-0.00276	-0.0120***
			(0.00195)	(0.00300)
F × LSurp × Dam2			-0.000601	-0.00753**
			(0.00274)	(0.00309)
PostF × HSurp × Dam2			-0.00214	-0.0107***
			(0.00312)	(0.00406)
PostF × LSurp × Dam2			-0.00856**	-0.00972**
			(0.00350)	(0.00399)
PostTrend × HSurp × Dam2			-0.00280***	-0.00678***
			(0.00105)	(0.00124)
PostTrend × LSurp × Dam2			0.00156	-0.00155
			(0.00108)	(0.00125)
F × HSurp × Dam3			-0.000564	-0.00982***
			(0.00173)	(0.00319)
F × LSurp × Dam3			0.00112	-0.00446*
			(0.00180)	(0.00261)
PostF × HSurp × Dam3			-0.00357	-0.0122**
			(0.00258)	(0.00479)
PostF × LSurp × Dam3			-0.00420	-0.00315
			(0.00278)	(0.00399)
PostTrend × HSurp × Dam3			-0.000159	-0.00412***
			(0.000863)	(0.00139)
PostTrend × LSurp × Dam3			0.00188**	-0.00134
			(0.000879)	(0.00128)
Observations	70,403	70,403	70,403	70,403
Within R-squared	0.007	0.02	0.019	0.041
X_{it} Controls	No	Yes	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1.Dam1/Dam2/Dam3 are indicators for the lower 33^{th} percentile/33^{th}-66^{th} percentile/upper 66^{th} of damage within the state. F is an indicator for flood event. PostF is an indicator for the period following the first year of impact. PostTrend is a linear trend starting the in the period following the impact. LSurp/HSurp is an indicator for a low/high surprise event. LGr/HGr is an indicator for positive/negative population growth 5 years prior to the event. Sample: 2000/2016. SE clustered by community. Additional controls: indicators for top 66^{th} perc. of fema/insured/business/sba damage; above median non-construction-based local economy; above median renter fraction; below 33^{th} perc. tot. damage. The estimation results do not report the coefficients for multiple-flood communities.

VARIABLES	(5) ln Pop_{ist}	(6) ln Pop_{ist}
F × HSurp × LGr ×Dam1	0.00739***	0.00615***
	(0.00151)	(0.00215)
F × HSurp × HGr ×Dam1	-0.00683***	-0.0166***
	(0.00203)	(0.00390)
F × LSurp × LGr ×Dam1	0.0202	0.00558
	(0.0129)	(0.00827)
F × LSurp × HGr ×Dam1	0.00349*	-0.00192
	(0.00199)	(0.00253)
PostF × HSurp× LGr ×Dam1	-0.00139	0.000660
	(0.00268)	(0.00441)
PostF × HSurp× HGr ×Dam1	-0.00679**	-0.0168***
	(0.00291)	(0.00586)
PostF × LSurp× LGr ×Dam1	0.0111	0.00513
	(0.0109)	(0.00755)
PostF × LSurp× HGr ×Dam1	0.00243	0.00149
	(0.00316)	(0.00431)
PostTrend × HSurp× LGr ×Dam1	0.00800***	0.00562***
	(0.000880)	(0.00115)
PostTrend × HSurp× HGr ×Dam1	-0.00368***	-0.00716***
	(0.000809)	(0.00149)
PostTrend × LSurp× LGr ×Dam1	0.00909***	0.00400***
	(0.00167)	(0.00149)
PostTrend × LSurp× HGr ×Dam1	0.000210	-0.00203
	(0.000919)	(0.00139)
F × HSurp × LGr ×Dam2	0.00732***	0.00627**
	(0.00180)	(0.00279)
F × HSurp × HGr ×Dam2	-0.00545**	-0.0159***
	(0.00234)	(0.00362)
F × LSurp × LGr ×Dam2	0.0126	-0.000747
	(0.00971)	(0.0100)
F × LSurp × HGr ×Dam2	-0.00372*	-0.00930***
	(0.00196)	(0.00278)
PostF × HSurp× LGr ×Dam2	0.00361	0.00499
	(0.00352)	(0.00567)
PostF × HSurp× HGr ×Dam2	-0.00372	-0.0149***
	(0.00371)	(0.00473)
PostF × LSurp× LGr ×Dam2	0.00129	-0.00434
	(0.00796)	(0.00834)
PostF × LSurp× HGr ×Dam2	-0.00985**	-0.0107**
	(0.00382)	(0.00458)
PostTrend × HSurp× LGr ×Dam2	0.00739***	0.00514***
	(0.000825)	(0.00121)
PostTrend × HSurp× HGr ×Dam2	-0.00572***	-0.00926***
	(0.00124)	(0.00143)
PostTrend × LSurp× LGr ×Dam2	0.0103***	0.00628***
	(0.00141)	(0.00162)
PostTrend × LSurp× HGr ×Dam2	-0.00115	-0.00364**
	(0.00127)	(0.00147)
F × HSurp × LGr ×Dam3	0.00429*	0.00324
	(0.00236)	(0.00324)
F × HSurp × HGr ×Dam3	-0.00279	-0.0130***
	(0.00206)	(0.00393)
F × LSurp × LGr ×Dam3	0.00315*	-0.00757
	(0.00187)	(0.00627)
F × LSurp × HGr ×Dam3	0.000665	-0.00429
	(0.00241)	(0.00331)
PostF × HSurp× LGr ×Dam3	0.000924	0.00185
	(0.00288)	(0.00481)
PostF × HSurp× HGr ×Dam3	-0.00578*	-0.0167***
	(0.00335)	(0.00620)
PostF × LSurp× LGr ×Dam3	-0.00569*	-0.0103
	(0.00331)	(0.00657)
PostF × LSurp× HGr ×Dam3	-0.00241	-0.000780
	(0.00358)	(0.00522)
PostTrend × HSurp× LGr ×Dam3	0.00470***	0.00259**
	(0.000762)	(0.00122)
PostTrend × HSurp× HGr ×Dam3	-0.00245**	-0.00580***
	(0.00111)	(0.00180)
PostTrend × LSurp× LGr ×Dam3	0.00758***	0.00357**
	(0.00107)	(0.00158)
PostTrend × LSurp× HGr ×Dam3	-0.000908	-0.00362**
	(0.00102)	(0.00164)
Observations	70,403	70,403
R-squared	0.061	0.081
X_{it} Controls	No	Yes

Table 11: Population and Real Estate Responses Controlling for Local Churches and Social Organizations

VARIABLES	(1) ln Pop_{ist}	(2) ln Pop_{ist}	(3) ln Pop_{ist}	(4) TopTier	(5) MiddleTier	(6) BottomTier
F	-0.0101***					
	(0.00230)					
PostF	-0.00948***					
	(0.00318)					
PostTrend	-0.00545***					
	(0.000970)					
F × HSurp		-0.0128***				
		(0.00244)				
F × LSurp		-0.00577**				
		(0.00287)				
PostF × HSurp		-0.0103***				
		(0.00336)				
PostF × LSurp		-0.00772**				
		(0.00362)				
PostTrend × HSurp		-0.00723***				
		(0.00101)				
PostTrend × LSurp		-0.00281***				
		(0.00104)				
F × HSurp × LGr			-0.00325	-0.0369***	-0.0261*	-0.0275*
			(0.00244)	(0.0125)	(0.0135)	(0.0160)
F × HSurp × HGr			-0.0141***	-0.00445	0.00703	0.0122
			(0.00246)	(0.00917)	(0.00930)	(0.0118)
F × LSurp × LGr			0.00341	-0.0183	0.00181	0.000337
			(0.00603)	(0.0143)	(0.0133)	(0.0169)
F × LSurp × HGr			-0.00758***	0.00145	0.0107	0.0114
			(0.00234)	(0.00961)	(0.00966)	(0.0120)
PostF × HSurp× LGr			-0.00501	-0.0545***	-0.0569***	-0.0694***
			(0.00356)	(0.0158)	(0.0177)	(0.0207)
PostF × HSurp× HGr			-0.0108***	-0.0127	-0.00556	-0.00958
			(0.00336)	(0.0118)	(0.0117)	(0.0144)
PostF × LSurp× LGr			-0.00213	-0.0249	-0.00689	-0.0321
			(0.00561)	(0.0183)	(0.0177)	(0.0205)
PostF × LSurp× HGr			-0.00808**	-0.00908	-0.0110	-0.0167
			(0.00348)	(0.0125)	(0.0125)	(0.0154)
PostTrend × HSurp× LGr			0.00124	0.00144	0.00518	0.00855*
			(0.00104)	(0.00379)	(0.00422)	(0.00500)
PostTrend × HSurp× HGr			-0.00858***	-0.00398	-0.00118	0.000514
			(0.00100)	(0.00281)	(0.00299)	(0.00339)
PostTrend × LSurp× LGr			0.00400***	-0.00438	-0.00366	0.00149
			(0.00120)	(0.00414)	(0.00427)	(0.00464)
PostTrend × LSurp× HGr			-0.00448***	-0.00474	-0.00207	0.000298
			(0.00105)	(0.00292)	(0.00299)	(0.00369)
F × Social	0.00222	0.00208	0.000223	0.00560	0.00552	0.0137*
	(0.00194)	(0.00194)	(0.00210)	(0.00581)	(0.00606)	(0.00729)
PostF × Social	0.00109	0.000896	-0.000535	0.0204***	0.0228***	0.0271***
	(0.00256)	(0.00255)	(0.00258)	(0.00753)	(0.00790)	(0.00959)
PostTrend × Social	0.00284***	0.00284***	0.00150**	-0.00265	-0.00318	0.000614
	(0.000711)	(0.000705)	(0.000680)	(0.00184)	(0.00201)	(0.00230)
Observations	70,403	70,403	70,403	61,530	60,920	54,554
Within R-squared	0.025	0.03	0.052	0.023	0.026	0.025
X_{it} Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1.F is an indicator for flood event. PostF is an indicator for the period following the first year of impact. PostTrend is a linear trend starting the in the period following the impact. LSurp/HSurp is an indicator for a low/high surprise event. LGr/HGr is an indicator for positive/negative population growth 5 years prior to the event. Social is an indicator for above median number of social organizations and churches per capita. Sample: 2000/2016. SE clustered by community. Additional controls: indicators for top 66^{th} perc. of fema/insured/business/sba damage; above median non-construction-based local economy; above median renter fraction; below 33^{th} perc. tot. damage. The estimation results do not report the coefficients for multiple-flood communities.

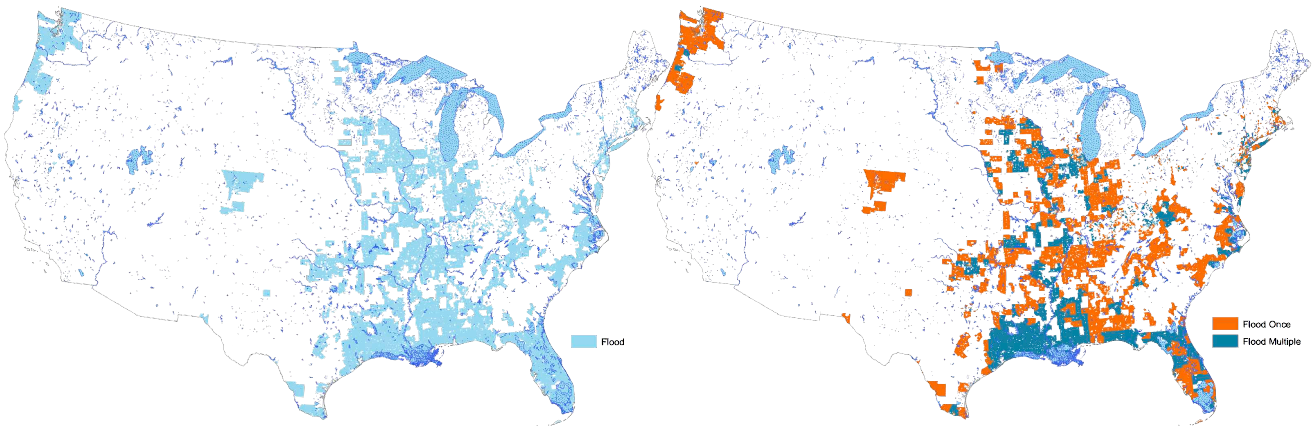

Figure 1: Locations with Single and Multiple Floods between 2003–2013

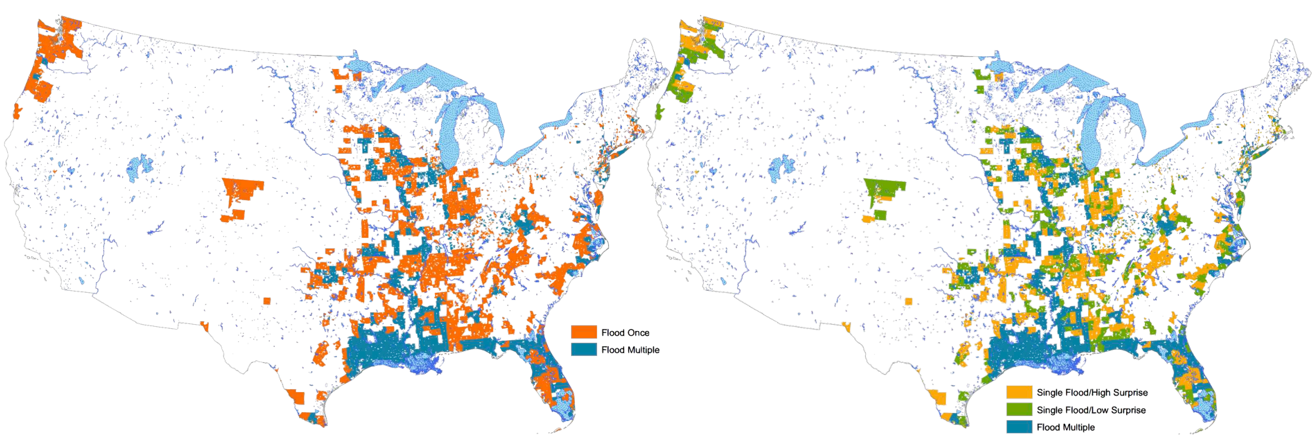

Figure 2: Locations with Flood Surprises between 2003–2013

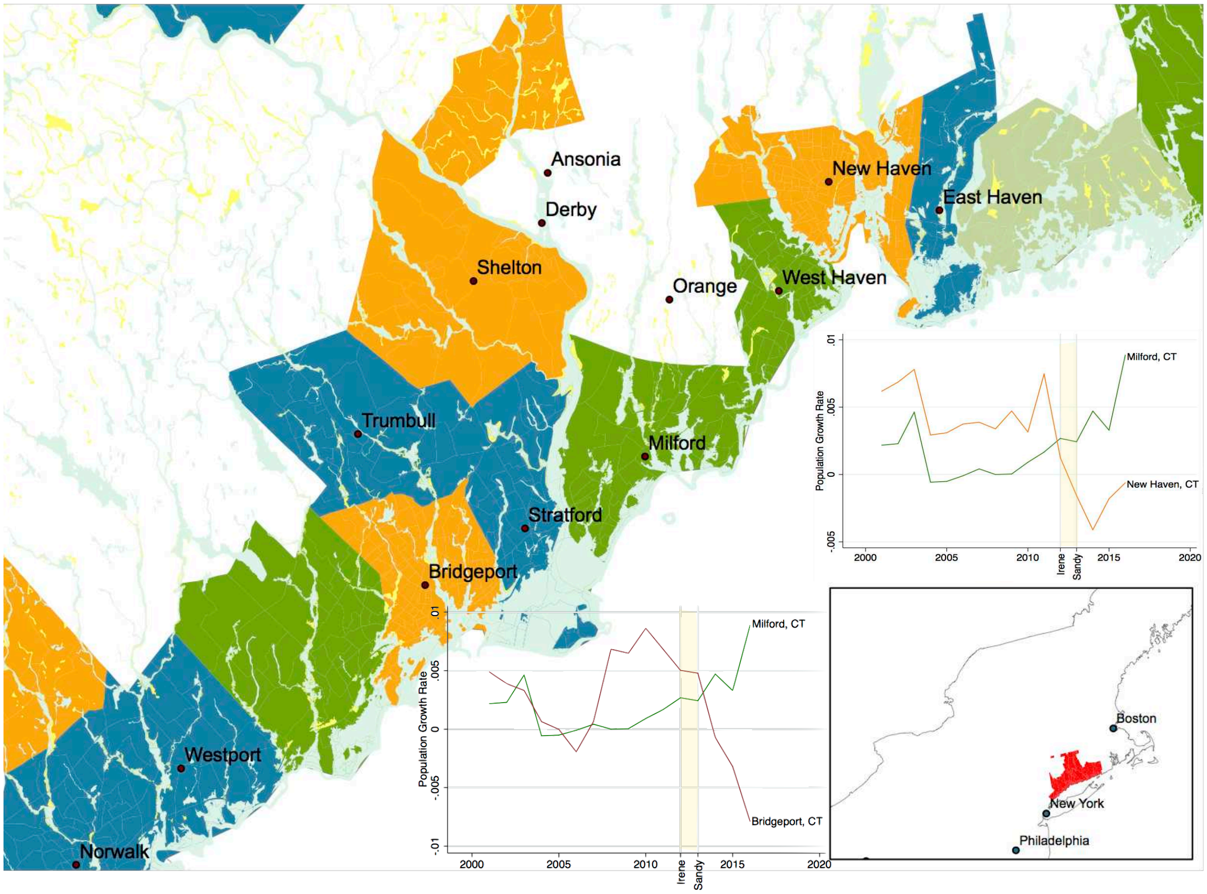

Figure 3: Population Growth of Milford vs New Haven and Bridgeport

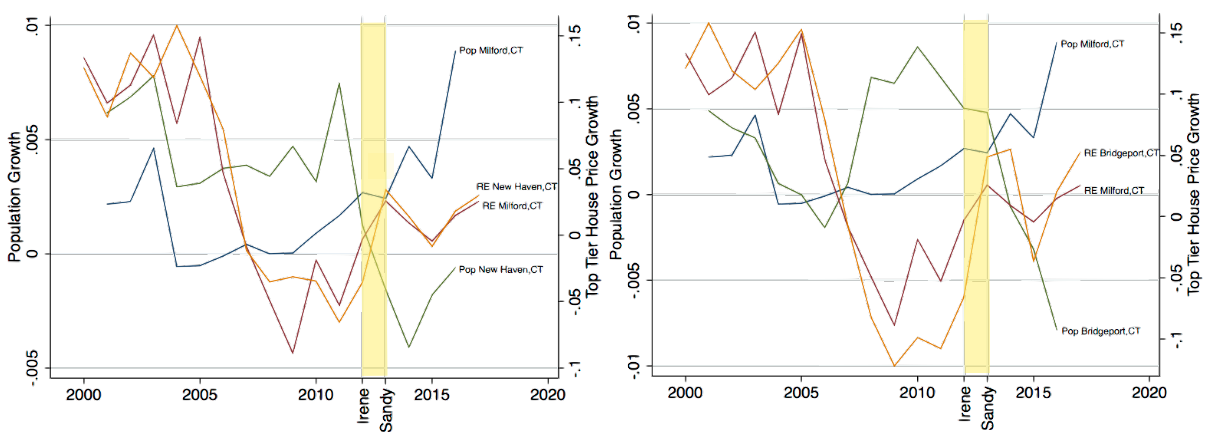

Figure 4: Population and Real Estate Values at Milford vs New Haven and Bridgeport

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Appendix 1: Additional Tables (for online publication only)

Table A1: Censor at 2bps – Flood Surprises and Population Changes

VARIABLES	(1) ln Pop_{ist}	(2) ln Pop_{ist}	(3) ln Pop_{ist}	(4) ln Pop_{ist}	(5) ln Pop_{ist}	(6) ln Pop_{ist}
F	-0.00147	-0.00709***				
	(0.000914)	(0.00187)				
PostF	-0.00385***	-0.00798***				
	(0.00131)	(0.00277)				
PostTrend	0.000180	-0.00290***				
	(0.000489)	(0.000875)				
F × HSurp			-0.00272**	-0.00872***		
			(0.00112)	(0.00211)		
F × LSurp			0.000434	-0.00486**		
			(0.00127)	(0.00192)		
PostF × HSurp			-0.00294*	-0.00781***		
			(0.00171)	(0.00301)		
PostF × LSurp			-0.00510***	-0.00832***		
			(0.00191)	(0.00305)		
PostTrend × HSurp			-0.00144**	-0.00448***		
			(0.000586)	(0.000915)		
PostTrend × LSurp			0.00242***	-0.000689		
			(0.000655)	(0.000979)		
F × HSurp × LGr					0.00669***	4.92e-05
					(0.00123)	(0.00212)
F × HSurp × HGr					-0.00526***	-0.0111***
					(0.00132)	(0.00217)
F × LSurp × LGr					0.00720***	0.00154
					(0.00267)	(0.00283)
F × LSurp × HGr					-0.00143	-0.00674***
					(0.00128)	(0.00195)
PostF × HSurp× LGr					0.00205	-0.00306
					(0.00183)	(0.00323)
PostF × HSurp× HGr					-0.00350*	-0.00894***
					(0.00209)	(0.00306)
PostF × LSurp× LGr					-0.000959	-0.00447
					(0.00278)	(0.00342)
PostF × LSurp× HGr					-0.00506**	-0.00869***
					(0.00240)	(0.00335)
PostTrend × HSurp× LGr					0.00688***	0.00350***
					(0.000557)	(0.000935)
PostTrend × HSurp× HGr					-0.00442***	-0.00681***
					(0.000681)	(0.000905)
PostTrend × LSurp× LGr					0.00876***	0.00552***
					(0.000771)	(0.000988)
PostTrend × LSurp× HGr					-0.000423	-0.00312***
					(0.000774)	(0.00104)
Observations	70,403	70,403	70,403	70,403	70,403	70,403
Within R-squared	0.007	0.024	0.012	0.029	0.04	0.051
X_{it} Controls	No	Yes	No	Yes	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1.This table replicates the main results in the paper using a higher cut-off for a flood event. Relative Damage below 2bps is censored. F is an indicator for flood event. PostF is an indicator for the period following the first year of impact. PostTrend is a linear trend starting the in the period following the impact. LSurp/HSurp is an indicator for a low/high surprise event. LGr/HGr is an indicator for positive/negative population growth 5 years prior to the event. Estimation (7) and (8) use a different definition for surprise – zero buildings destroyed between 1978 and 2003. Sample: 2000/2016. SE clustered by community. Additional controls: indicators for top 66^{th} perc. of fema/insured/business/sba damage; above median non-construction-based local economy; above median renter fraction; below 33^{th} perc. tot. damage. The estimation results do not report the coefficients for multiple-flood communities.

Table A2: Drop over 8.66% Relative Damage – Flood Surprises and Population Changes

VARIABLES	(1) $\ln Pop_{ist}$	(2) $\ln Pop_{ist}$	(3) $\ln Pop_{ist}$	(4) $\ln Pop_{ist}$	(5) $\ln Pop_{ist}$	(6) $\ln Pop_{ist}$
F	-0.000997	-0.00933***				
	(0.00112)	(0.00202)				
PostF	-0.00388***	-0.00926***				
	(0.00144)	(0.00277)				
PostTrend	-8.65e-05	-0.00414***				
	(0.000483)	(0.000853)				
F × HSurp			-0.00325***	-0.0121***		
			(0.00120)	(0.00241)		
F × LSurp			0.00273	-0.00501**		
			(0.00193)	(0.00231)		
PostF × HSurp			-0.00456***	-0.0103***		
			(0.00174)	(0.00311)		
PostF × LSurp			-0.00250	-0.00739**		
			(0.00217)	(0.00308)		
PostTrend × HSurp			-0.00144**	-0.00580***		
			(0.000582)	(0.000907)		
PostTrend × LSurp			0.00196***	-0.00167*		
			(0.000617)	(0.000934)		
F × HSurp × LGr					0.00649***	-0.00319
					(0.00115)	(0.00245)
F × HSurp × HGr					-0.00567***	-0.0143***
					(0.00142)	(0.00243)
F × LSurp × LGr					0.0117**	0.00327
					(0.00543)	(0.00505)
F × LSurp × HGr					-6.37e-05	-0.00767***
					(0.00131)	(0.00209)
PostF × HSurp× LGr					0.000959	-0.00539
					(0.00190)	(0.00332)
PostF × HSurp× HGr					-0.00526**	-0.0113***
					(0.00206)	(0.00314)
PostF × LSurp× LGr					0.00253	-0.00279
					(0.00484)	(0.00474)
PostF × LSurp× HGr					-0.00312	-0.00818***
					(0.00211)	(0.00317)
PostTrend × HSurp× LGr					0.00697***	0.00223**
					(0.000594)	(0.000889)
PostTrend × HSurp× HGr					-0.00405***	-0.00785***
					(0.000655)	(0.000914)
PostTrend × LSurp× LGr					0.00893***	0.00488***
					(0.000883)	(0.00105)
PostTrend × LSurp× HGr					-0.000818	-0.00413***
					(0.000694)	(0.000969)
Observations	70,403	70,403	70,403	70,403	70,403	70,403
Within R-squared	0.003	0.024	0.007	0.029	0.042	0.056
X_{it} Controls	No	Yes	No	Yes	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1.This table replicates the main results in the paper by dropping communities with more than 8.66% relative damage. For additional details see Table A1

Appendix 2: Data Construction (for online publication only)

NFIP maintains an official record of the number of policies sold, total coverage, and total payouts at the level of a given community since the program effectively partners with the local authority enforcing the flood map and building code. The geographical level is consistent with the US Census definition of general-purpose government units such as cities, towns, townships, as well as the remaining county areas (county balance). I focus on 38 states with FEMA disaster declarations related to flooding. Table 1 lists the states considered. Median population across the 4,147 communities in 38 states in the sample is 34 thousand people. Insurance information includes homeowners and business structures.

NFIP does not list payouts associated with particular flood events. Instead, it shows up-to-date payouts starting from 1978. I use historical observations of the official record taken approximately twice a year between 2003 and 2014 to calculate the amount of new payouts claimed at each community. These represent insured damages associated with flood events during each year. I carefully link the observed payouts to the set of FEMA disaster declarations for each state. The matching was not automated but involved reading the description of FEMA declarations for each state/year and associating flood events in the covered counties to observed insurance payouts at communities in those counties. This link allows me to identify both the amount of insured and uninsured damages for each FEMA event. In approximately 25% of community/year cases total losses are based only on insured damage. This is consistent with the fact that not all communities in counties with disaster declarations will have significant uninsured losses.

The uninsured damages are sourced from FEMA's individual/public assistance data and from Small Business Administration's (SBA) individual/business lending data. A disaster declaration makes federal funding available to affected individuals without insurance. They can receive either a direct non-refundable payment or a highly subsidized loan depending on their ability to take on additional credit. FEMA administers the direct payments and SBA extends the loans. Both maintain a registry that identifies the amount of assistance provided and the related total damage at the zip-code level for each disaster declaration. Altogether, total damage in the data has four components: insured individual/business from NFIP; uninsured individual from FEMA and SBA; uninsured business from SBA; uninsured public from FEMA. In this paper I focus primarily on total damage. The components are only used to control for events where most of the damage comes from one of the source.

Relative damage is calculated using an estimate for the total value of the real estate during the year of a flood. The value is calculated using information from the 2000 Census at the block level. I add the total housing values listed in the Census across all of the value categories for a total real estate value in 2000. I then use the annual state house values from the FHFA to project the 2000 values forward for each year.

Zip-code data is associated to community-level data using block-level population weights. In particular each Census block lists the total population, the zip-code, and the community. This allows me to assign zip-code values to communities by appropriately weighting using population.

Data on flood insurance policies is only available for the years of 2002-2006 and 2010.

This is due to a change in the way data was reported across the years.

Fraction of population in a flood zone has been calculated by overlaying community flood zones with census blocks from the 2000 Census. I have used area as weights to assign the 2000 population from each block in or outside of the flood zone.