Weather Shocks, Housing Prices, and Population: the Role of Expectation Revisions

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Abstract

This paper studies how expectations of future flood risk in communities within the U.S. changes once they experience a flood. Focusing on small events, I examine if population and housing values change in a way consistent with higher flood risk. To do this, I compile a new measure of insured and uninsured losses for 4,147 locations and identify small flood events at places with different flood history. I show that flood history determines the extent to which events are anticipated and covered by insurance. Only flood surprises cause declines in population. These occur in attractive communities with high pre-flood growth where housing prices do not compensate for higher risk. Flood surprises in communities where housing prices decrease and compensate for higher risk have stable population.

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1 Introduction

Flooding is a frequent concern across the US since damage to buildings and equipment is hard to reverse. This is why the US Government maintains a subsidized flood insurance program which conveys local risk through designated flood zones. Changes in severity of weather events and new construction can shift flood risk beyond these zones. When communities with limited previous exposure experience a flood for a first time, they will have to determine whether it constitutes a rare event or a change in the underlying risk of flooding. Distinguishing between these two possibilities is challenging yet really important because mistaking changes in flood risk for rare events can expose these communities to significant future damages. There is limited empirical evidence about whether communities tend to disregard flood surprises as rare events or respond as if the underlying flood risk has changed. Studies of the aftermath of major hurricanes cannot shed light on this since the significant effect on housing and local productivity confounds the impact of changes in risk.

This paper examines whether unexpected flooding leads to changes in local population and real estate values consistent with increases in underlying flood risk. Importantly, I mitigate the confounding effects of housing supply and productivity shocks by focusing on events that cause limited damage to the community. When the housing stock of the community is virtually unaffected, any resulting change in population and house prices must come from changes in perceived future risk. The existence of flood insurance and local flood regulation allows for two different joint responses consistent with higher risk. On one hand, risk can be offset with insurance or upgrades of existing structures which raises the cost of living and reduces population. On the other hand, the durability of existing houses makes population less sensitive to increases in risk since house prices will compensate for the insurance cost. Consequently, both stable population with reduced house prices and decreased population with stable house prices are consistent with higher perceived risk, while lack of response implies no change in perceived risk. These responses are distinct from the case of significant damage which is not considered in this study. In this instance we are likely to see a sizable decrease in population on impact and higher real estate prices.

Identifying flood surprises with limited overall damage requires detailed local data on current and historical damages. This study uses a newly collected information on insurance payouts at the level of census-designated place for the entire U.S. between 2003 and 2013.[1] Importantly, the information includes historical payouts and number of structures destroyed by floods starting from 1978. This makes it possible to separate out communities with limited historical experience with flooding. I also collect information on uninsured local damages which allows me to identify the overall damage from a flood. Accounting for both insured and uninsured damages, this is the first effort to compile an estimate of total damages due to flooding at such a granular level for the entire country. I match the flood data to a panel of annual census-based population and local real estate values from Zillow. The panel setting is critical in identifying the effect of perceived risk separately from a variety of factors that can affect population and real estate prices before and after a flood. In particular, I allow for: permanent differences across communities; community-specific linear trends; state-year-specific factors; differential responses of communities according to their level of uninsured damage, industrial composition, and share of renters. The latter is critical since places with different damage and industries are likely to respond differently to flood surprises.

First, I show that historical damages provide a good measure for perceived flood risk in a community. I use the number of buildings destroyed by floods between 1978 and 2003 as a fraction of total buildings in 2003 relative to the state median to define the level of historical flood experience. I find that perceived flood risk is related to this measure. Locations with high flood history have a higher footprint in a flood zone, more insurance purchases, and a higher insurance coverage. They get 23% more insurance payouts after a flood, 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. Communities with low historical flood experience purchase less insurance and receive more relief

[1] The dataset includes a total of 4,147 communities in 38 states which experience floods.

funding following flood events indicating that these events are not anticipated.

Second, I examine the effect on population and real estate values by focusing on places that have a flood once between 2003 and 2013.[2] This allows for a clear pre and post period and excludes locations that flood frequently. Damages among the remaining single-flood communities are relatively low: the 95^{th}, 97^{th}, and 98^{th} percentiles of flood events affect 1%, 1.9%, and 2.9% of the local housing stock. In this case flooding in a community with historical damages is neither a rare event nor does it lead to increases in perceived risk. Not surprisingly, I find no evidence that population and house values are affected after a flood. This is consistent with the higher insurance coverage and with population sorting emphasized by Bunten and Kahn (2014). Smaller floods seem to not be sufficient to raise risk expectations in communities with history of damages.

In the case of communities that experience flood surprises I find evidence that population and real estate values respond in a way consistent with increases in flood risk. In a simple specification, population in the year following the surprise 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 compounded long-term impact. With controls for the composition of the damage and community characteristics the impact is substantially higher: 1.2% initial drop and 0.6% lower pre-flood trend. This overall negative effect on population conceals a significant heterogeneity that exists within locations with flood surprises. When I condition on pre-flood population growth and allow different population responses for growing communities and non-growing ones I find that the attractive locations suffer from a significant drop in population. The less attractive communities experience virtually no change in population relative to their pre-flood fixed effect and linear trend.

At first glance, the results suggest that less attractive locations tend to consider flood surprises as providing no additional flood risk information while attractive ones seem to increase perceived flood risk. This requires that real estate prices do not adjust in the less

[2]Two consecutive floods are classified as a single flood event since a clear pre and post period can be defined.

attractive locations. The evidence suggests that this is not the case. These locations see close to a 4% drop in real estate values, with the biggest effect among expensive housing. This is consistent with evidence from Glaeser and Gyourko (2005) where adjustments in house values can limit population changes. The fact that more expensive housing declines echoes Boustan et al. (2017) and Strobl (2011) who find that high-income individuals leave affected communities. Interestingly, in the attractive communities house prices do not decline, 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.[3] This is likely to be the case in growing communities where price is above replacement cost as shown by Gyourko and Saiz (2004).

All together, the results suggest that flood surprises affect communities in a way consistent with increases in flood risk. At the same time, similar small events do not affect locations with previous exposure to flooding. Importantly, higher flood risk does not have a uniform effect on all communities. In places where demand for housing is low, existing structures are sold at a discount that covers the additional cost of living. 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 experience with flooding leads to the institution of local preventive measures such as zoning, which requires mandatory insurance coverage. Consequently, additional flooding is

[3] Homeowners likely raise existing structures to decrease insurance premiums and do general home improvements at the same time.

in line with expectations and only generates insurance payouts. Flood surprises, on the other hand, deviate from expectations and raise flood risk. Even without significant productivity and/or house supply reduction, higher risk reduces the total number of people that choose to live there. The pre-flood growth determines where population falls the most: places with strong demand for new housing experience population declines; places with weaker demand see lower house prices.

The rest of the paper is structured as follows. Section 2 discusses related literature and contributions. Section 3 explains the institutional details of the flood insurance program and describes how the flood data was compiled. Section 4 presents the main results. Section 5 examines the regional heterogeneity of the main results. Section 6 includes extensions and robustness and Section 7 concludes the paper.

2 Related Literature

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 of 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 to 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 environmental risks on population and housing. The former finds compensating declines in real estate values, while the latter two find a negative association between population and health risk. Albouy et al. (2016) studies the preference for climate and how climate change will affect welfare across the US.

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 and hurricane paths. Boustan et al. (2012, 2017) studies the impact of disasters historically and over a long period of time and finds negative population effects. 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. The current study extends this literature by unpacking the composite effect of a natural disaster and focusing on the risk channel. It emphasizes the importance of pre-existing expectations and the availability of insurance. It shows that underlying factors that affect the attractiveness of the community interact with risk revisions and determine whether population or house values are ultimately impacted.

Relative to the literature on natural disasters, the analysis uses a newly collected data at a more granular level while still covering the whole country. More detailed data is critical when studying the impact of natural disasters because, as the current study shows, different communities within counties have markedly different experience with flooding. This leads to significant differences in preparedness and insurance coverage which ultimately affects the extent of damages that each community will suffer.

This paper is also 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.

3 Flooding Dataset and Institutional Details

In order to properly measure the overall impact of an event one needs to account for both insured and uninsured damage. The existing literature on natural disasters does not utilize actual recorded damages but generally uses estimates based on disaster declarations across counties and hurricane paths. Since most of hurricane damage comes from flooding and the extent of flooding depends on the amount of local construction and geographical characteristics, the amount of actual damage can vary significantly within counties and across hurricane paths. An important part of the data-building exercise here is to carefully construct an estimate of total damages.

Flood insurance in the US is administered by the federal government through the National Flood Insurance Program (NFIP). The program makes insurance available to 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. Importantly, the risk within the 500-year and 100-year SFHA is not uniform – local geographic characteristics will make some areas more likely to flood. Insurance purchase is mandatory for mortgaged structures within the 100-year zone but not required otherwise. This is important because risk expectations rather than local regulation will determine the insurance purchase in that case. Kousky

(2018) provides an in-depth discussion of the NFIP.

The flooding dataset is based on the NFIP's insured damage and on the FEMA/Small Business Administration (SBA) information on uninsured damage. The sample covers 38 US states because those have disaster declarations related to flooding. Data is aggregated at the census-designated place level (communities for short), 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. 75% of community/year cases feature total losses 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. Here, 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. Finally, I have limited information on the number of policies and total coverage for a subset of years in the sample. Appendix A2 has additional information about the data.

Population information comes from the annual US Census estimates for cities and towns. The geographical detail of this data maps directly into the census-designated place 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.[4] 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

[4]This is a standard approach and is utilized in Banzhaf and Walsh (2008)

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% and after dropping locations with damage over 8.66%.

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 experience repeated disasters during the sample period. They are separated 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 structures that were completely destroyed due to flooding between 1978 and 2003. Note that I also 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. The occurrence of a flood there is assumed to generate a surprise. 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 where the surprise category is not state-specific, I assume that high surprise are only communities with zero lost structures. While this reduces the number of high-surprise communities it ensures that when floods occur they 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 flooding. 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 by the number of floods while Table 2 does this by categories of communities. Note that, for the case of single floods, the 95^{th} percentile of relative damage is 1%. The 97^{th} and 98^{th} percentiles are 1.9% and 2.9% correspondingly. 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 (1,771 vs 1,519). This reflects the fact that the sample excludes 12 states and that flooding is a widespread phenomenon. These groups have similar population, income, growth, and housing values. The no-flood group has a smaller footprint in a flood zone and less active insurance policies. The single-flood group with low historical flooding (high surprise) is similar to the no-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 the 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.

4 Main Results

The historical experience of a community is critical in understanding how new floods will affect its size and real estate values – only flood surprises are likely to results in any changes. Yet, even in these cases it is possible that surprises are interpreted as rare events and result in no adjustment in the community, particularly because damages are small. This section first looks at how insurance coverage and payouts vary with historical flood experiences in the cross-section of events. Following that I use the full panel and examine whether flood surprises lead to changes in size and real estate values consistent with updated flood risk.

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 examines 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 – wholly owned within the 100-year zone or outside – depend on the perceived risk of a flood. High flood history increases perceived risk and leads to insurance purchase. I examine this relationship by comparing the average insurance payouts across the high- and low-flood history groups in the cross-section of all events. If flood history does not affect the extent to which floods are anticipated we should not see differences in insurance coverage across these groups. I test this relationship by estimating:

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

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, 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.[5] Positive γ implies that the same damage generates more payouts in low surprise communities. Additionally, I estimate the above model without controlling for damage. In that case γ represents the additional insurance payouts generated during an average flood event at communities with history of flooding. Finally, I 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 have significantly higher insurance payouts per capita during an average flood event (model 1). This is consistent with the higher number of active insurance policies observed. These locations receive almost double the insurance compensation relative to locations with low history. Model 2 of Table 3 explores the regional heterogeneity. High history is associated with higher in-

[5]Note that for the single-flood locations i represents both the community and the event whereas for the multiple-flood locations it represents a particular event at a given community.

surance payout in all six 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. Since this specification does not control for damage, the low surprise events in those regions likely have more insurance payouts because the events are generally more damaging. Model (3) controls 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 have 50% more of their damage covered through insurance compared to the rest. Note that low flood communities still have insurance coverage since they also have flood zones. Yet, the coverage is smaller since their flood zones are not sufficiently big and/or residents choose to not buy insurance. Model (4) shows that this result is consistent across regions of the US. Models (5) and (6) show that affected low-surprise locations have more active insurance policies. In fact, even though the active-policies sample is smaller the difference between the number of policies and payouts is remarkably similar.

Overall, the results provide further confirmation of the group differences observed in the summary statistics. They show that more people live in a flood zone in communities with high flood experience. The bigger zones are likely a result of the past flood history. Nevertheless, if communities in both groups anticipate flood events equally we would not observe differences in the insurance coverage since the low-history communities will choose to buy insurance outside of the flood zones. The fact that even at the same damage level low history places have lower insurance coverage suggests that they discount existing flood risk. The results also suggest that high damages do not necessarily imply big losses for the community since these may be covered by insurance depending on its history.

Population Responses

Since the majority of events that hit the single-flood group have a low impact, it is possible that even when they occur at places with no previous flooding they will not affect perceived risk. As a result we may see that they have no impact regardless of whether they are surprises or not. I first examine the effect on population by estimating 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 a community average, α_i, community linear trend, t_i, and a state-year effect, γ_{st}. This specification is flexible enough to allow for time-invariant differences in settlement size and community-specific differences in the population growth.[6] Allowing for a community fixed effect implies that any constant factors that explain why a community is bigger or smaller will not explain population responses to floods. Similarly, location-specific linear trends imply that factors that affect the overall population growth of the community will not explain flood responses. These responses are identified if each affected community experiences a similar deviation from its own population average and pre-food growth. It is possible that places with higher uninsured damage, higher share of renters, and more developed local economy respond differently. I do allow for this as explained below. Finally, the state-year effect captures variations in local population which can be traced to the state/national level.[7] 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 they experience. For 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, $PostTrend_{it-2}$. The multiple-flood group includes 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

[6] For a discussion of size and trend-difference see Desmet and Henderson (2014) and Desmet and Rappaport (2017).

[7] Blachanrd and Katz (1992) discuss the important differences in population patterns across sates.

more straightforward. Note that communities with two consecutive-year events are classified as single-hit. 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 indicators that have been interacted with F_{it-1}, $PostF_{it-2}$, and $PostTrend_{it-2}$. These include indicators based on the state distribution 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. Both of these are expected to lead to increases in population after a flood. The second controls for the capacity to accommodate the displaced from floods, as well as emergency or temporary workers. This can also lead to increases in local population even if the community is hit by a flood. The 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 model assumes that flood surprises are not relevant. I extend this by allowing for different responses across the high/low history communities. Finally, I separate the impact by pre-flood population growth (last five years). Growing locations attract more newcomers 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 an urban status. For example, urban communities 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 the paper emphasizes the effect of existing positive net migration – a higher-frequency shock – and simply control for the time-invariant differences.

I also estimate the model using a stricter criterion for the high-surprise category – including only locations with no building destruction in the past 25 years. This limits the number of high-surprise communities but ensures that the occurrence of a flood 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 in model (1) is not affected by a flood. The average location from model (2) with a 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 0.4% decline in the pre-flood trajectory. The difference in results comes from the fact that the composition of the local economy, the availability of rentals, and the share of FEMA-recorded 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.[8] Overall, model (2) shows that flooded places with lower rental share, higher construction occupations share, and intermediate damage shares see a decrease in expected

[8]Kahn (2009) points out that urban areas can experience population growth after a flood because the city infrastructure provides safety. Since urban areas have more diversified economies and higher renter shares, I implicitly account for this.

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 models (3) and (4). The evidence shows that population declines are significantly stronger in communities that experience a flood suprise. An average location from (3) is only affected when the flood is unexpected. On impact, population drops 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. More specifically, we see that floods in locations with limited previous experience generate a response consistent with increased risk i.e. they are not disregarded as rare events. This is consistent with the insurance results and suggests that revisions of flood risk disrupt the pre-flood population dynamic. 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. Results from (3) and (4) provide strong evidence that population declines when a flood is unexpected. While the initial decline in population is persistent it is still relatively small at 1%. This is consistent with the low impact that these events have on the housing stock. 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. This implies that the effect stems from revisions of risk expectations. Consequently, the biggest population changes will not necessarily overlap with biggest damages. Note that flooding seems to lead to some population increases in places with more diversified local economies and more rental capacity. The result is consistent with findings in Boustan et al. (2012), who show that floods actually increase population. This effect can offset the decline in population 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 estimate separately the impact for locations with positive (constant) 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 non-negative 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 suggests that the population decline is related to 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 flood events are ignored as rare events or that the real estate values decline and compensate for higher risk. I explore this question in the next section.

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 possible that the observed interaction between pre-flood growth and flood surprises is due to differences in income or local land-use regulation, not in the growth per se. For example, weak regulation may be driving growth in locations that ultimately see higher flood risk. Revisions of risk, therefore, may be more impactful where regulation is low. Alternatively, strong regulation can significantly limit new construction and make the repair of existing structures very costly. This can lead to higher population impact in highly-regulated communities. Similar concern exist across communities with different income level. I explore these alternatives in the robustness section. The evidence generally suggests that they are not able to explain why population decreases after a risk revision.

It is important to point out an issue that relates to the possible endogeneity of flooding and an unobservable local economic factor. It is possible that such a factor causes communities to invest less in flood protection and ultimately causes bigger damages. Here it really matters how this factor is related to the population trajectory before and after the flood. If it causes population to be decreasing before the flood then I incorporate this in the model by allowing location-specific trajectory before the flood. If it cause population to respond differently only after the flood then it is hard for me to disentangle the effect. I accommodate this possibility with a set of controls in X_{it-1}.

Real Estate Responses

In this part 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 seemingly 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 choose other locations, which limits the size of the community.

In the case of low-growth location the evidence shows a clear decline of house values after a surprise. Top and middle-tier housing decrease by 2.3%-3.4% on impact; the dip is persistent and remains 4.4% lower 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 suggests that the constant population does not imply that flood surprises are irrelevant for perceived flood risk. In these communities, low demand for additional housing leads to higher sensitivity of housing values and lower sensitivity of population. House values decline and 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. The fact that more expensive houses take the brunt of the adjustment indicate that the higher-wealth population likely leaves the community. This is consistent with findings by Boustan et al. (2017) and Strobl (2011) who show that high-income individuals leave communities affected by disasters.

All together the housing and population results suggest the following interpretation.

Flooding in places with previous experience does not generate changes in perceived risk and does not cause changes in population or house values. In contrast, 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.

Going back to the example at the beginning of the section, Figure 4 shows the evolution of population and real estate for Milford and the two neighbors. 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.

5 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 no effect elsewhere. Additionally, since the joint response of population and real estate help understand the impact of surprises, 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 Census regions.[9]

The regional results for population are listed in Table 6. The coefficients reported in the table are all based on 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 declines at high pre-growth/low surprise communities seen in the main results are only identified in the Northeast region. 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 7. 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. The lack of compensating decreases in housing and the simultaneous decrease in population at these locations across all regions supports the interpretation in the main results. It suggests that these communities become relatively more expensive everywhere. 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. Risk awareness in these communities can facilitate population sorting which can minimize the sensitivity of population and housing values to

[9] I have split region 1 into Northeast and Mid-Atlantic and region 3 into South Atlantic and South Central.

risk revisions. This point is discussed in Bunten and Kahn (2014). The authors point out that incumbents, who have sorted into high-risk locations, may be better at dealing with disasters and value local amenities highly enough so that risk revisions do not alter the relative attractiveness of their current location.

Housing depreciates in low pre-growth communities in all regions except for the Midwest and South Central. The reduction in real estate values paired with the minimal changes in population is consistent with the interpretation in the main results. Durable housing compensates for the increased risk and leaves population unchanged. In the case of the Midwest and South Central there are both minimal population changes and no price adjustment. Living in these areas effectively becomes more expensive since the real estate does not provide compensation. The evidence from the FEMA payments in the next section 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. In the case of the Midwest region it appears that flood surprises do not lead to increases in perceived risk but are regarded as rare events.

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.

6 Extensions and Robustness

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 8. 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.

Flood Spillovers

Floods can have an effect on other locations that may not themselves be affected. Gallagher (2014) shows that insurance purchases pick up after floods at locations within the same media market. 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 to differ for places neighboring 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 but are not themselves affected. The literature on natural disasters imputes damages based on wind gradients and hurricane paths. It is likely that some of the locations do not sustain damages but are assumed to be affected. The results here help us understand how this influences these estimates.

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. Note that the spillover effect is smaller than the direct effect. This is consistent with an increase in perceived risk since the spillover is based on locations without direct damage. 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 for unaffected locations. 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 somewhat 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.

Land-use Regulation and Income

The paper emphasizes the importance of pre-flood positive net migration and its interaction with flood surprises. Here I also explore whether the local housing supply elasticity or the local income level can explain the observed population patterns. For house elasticity, I use the Wharton Residential Land Use Regulation Index (WRLURI) from Gyourko et al. (2007). I am able to match a third of the baseline sample with the WRLURI and this limited sample. Locations with above state-median values for the index are considered to be highly regulated. For the case of local income, I use the 2000 Census and assign locations based on the state median income. Results are listed in Table 12. Estimations (2) and (4), which include X_{it} controls, show that land regulation and income cannot fully explain the population declines. Namely, flood surprises reduce population both in locations with high and low regulation. However, the observed effect in the high-regulated communities is higher, suggesting that a contraction in the supply of new construction is a part of the reason why population declines. It is likely that highly-regulated places will reduce the construction of new houses more than low-regulated ones when flood risk increases. The estimates in (2), therefore, suggest that some of the observed population decline is due to lower housing supply. The interaction of income with flood surprise is also not able to completely explain the population declines – both high and low income places are affected after a flood.

7 Conclusion

This is the first study that examines the effect of flood surprises using consistent national data of insured and uninsured damages at the level of the community. It investigates whether communities respond to surprises in a way consistent with increases in perceived risk. In particular, I examine how the local population trajectory and real estate values are affected. I find that risk expectations do not appear to be changed from smaller floods in locations with previous experience. This indicates that flooding is widely expected and the local population is already somewhat insulated from the risk with insurance. In places with no experience flood surprises increases perceived risk. These locations 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 newcomers steering away. Less attractive locations see predominately house price declines and stable population. Interestingly, the regional results suggests that the Midwest region is the only area within the country where flood surprises do not lead to increases in flood risk. Using these results to interpret how climate change will affect communities within the US, we expect to see three general local outcomes. 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%	1.03%
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 ($1 mil)

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: 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 7: 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 8: Low-wealth Incidence in Low-Growth Communities

	(1)	(2)
VARIABLES	ln($FemaPay$)	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 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)
$F^{Neighbor}$		-0.00975**				
		(0.00427)				
$PostF^{Neighbor}$		-0.00469				
		(0.00545)				
$PostTrend^{Neighbor}$		-0.00375**				
		(0.00168)				
$F^{Neighbor}$ × HSurp			-0.00862*	-0.0301**	-0.0354***	-0.0195
			(0.00480)	(0.0143)	(0.0135)	(0.0165)
$F^{Neighbor}$ × LSurp			-0.00936**	-0.0250**	-0.0282***	-0.0176
			(0.00420)	(0.0103)	(0.0105)	(0.0122)
$PostF^{Neighbor}$ × HSurp			-0.00670	-0.0234	-0.0552***	-0.0525***
			(0.00602)	(0.0182)	(0.0158)	(0.0182)
$PostF^{Neighbor}$ × LSurp			-0.00115	-0.0370***	-0.0614***	-0.0657***
			(0.00570)	(0.0142)	(0.0144)	(0.0165)
$PostTrend^{Neighbor}$ × HSurp			-0.00593***	-0.00461	0.00138	0.00425
			(0.00180)	(0.00451)	(0.00398)	(0.00460)
$PostTrend^{Neighbor}$ × 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. $F^{Neighbor}$ is an indicator for a community with no flooding located in county with a single flood only. $PostF^{Neighbor}$ and $PostTrend^{Neighbor}$ 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.

Table 12: Land-use Regulation Index and Income

VARIABLES	(1) ln Pop_{ist}	(2) ln Pop_{ist}	(3) ln Pop_{ist}	(4) ln Pop_{ist}
F × HSurp × L Regulation	-0.00162	-0.0101**		
	-0.00247	-0.00414		
F × HSurp × H Regulation	-0.00959***	-0.0186***		
	-0.0031	-0.00481		
F × LSurp × L Regulation	0.00228	-0.00976**		
	-0.00235	-0.00433		
F × LSurp × H Regulation	0.000892	-0.00812*		
	-0.00314	-0.00452		
PostF × HSurp× L Regulation	-0.00373	-0.00878		
	-0.00351	-0.00544		
PostF × HSurp× H Regulation	-0.00837**	-0.0142**		
	-0.0041	-0.00634		
PostF × LSurp× L Regulation	-0.00414	-0.0128**		
	-0.00405	-0.00634		
PostF × LSurp× H Regulation	-0.00674	-0.0132**		
	-0.00468	-0.00631		
PostTrend × HSurp× L Regulation	-0.000536	-0.00636***		
	-0.00126	-0.0018		
PostTrend × HSurp× H Regulation	-0.00558***	-0.0113***		
	-0.0015	-0.00237		
PostTrend × LSurp× L Regulation	0.00137	-0.00486**		
	-0.00135	-0.00207		
PostTrend × LSurp× H Regulation	0.00249	-0.00227		
	-0.00159	-0.00208		
F × HSurp × L Income			-0.000634	-0.00988***
			-0.00117	-0.00234
F × HSurp × H Income			-0.00679***	-0.0167***
			-0.00223	-0.00307
F × LSurp × L Income			0.00485*	-0.0039
			-0.00288	-0.00284
F × LSurp × H Income			0.000459	-0.00752***
			-0.0018	-0.00264
PostF × HSurp× L Income			-0.00360**	-0.00942***
			-0.00176	-0.00307
PostF × HSurp× H Income			-0.00597*	-0.0126***
			-0.00327	-0.00426
PostF × LSurp× L Income			-0.000678	-0.00617*
			-0.00293	-0.00334
PostF × LSurp× H Income			-0.00490*	-0.0101**
			-0.00295	-0.00406
PostTrend × HSurp× L Income			0.000529	-0.00424***
			-0.000611	-0.000901
PostTrend × HSurp× H Income			-0.00468***	-0.00919***
			-0.000983	-0.00126
PostTrend × LSurp× L Income			0.00294***	-0.00145
			-0.000699	-0.000965
PostTrend × LSurp× H Income			0.00101	-0.00235*
			-0.000957	-0.00123
Observations	23,747	23,747	70,403	70,403
Within R-squared	0.024	0.063	0.015	0.033
X_{it} Controls	No	Yes	No	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. L Regulation/H Regulation is an indicator for below/above state-median regulation of the local land use based on the Wharton Residential Land Use Regulation Index. L Income/H Income is an indicator for below/above state-median income from the 2000 Census. 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.

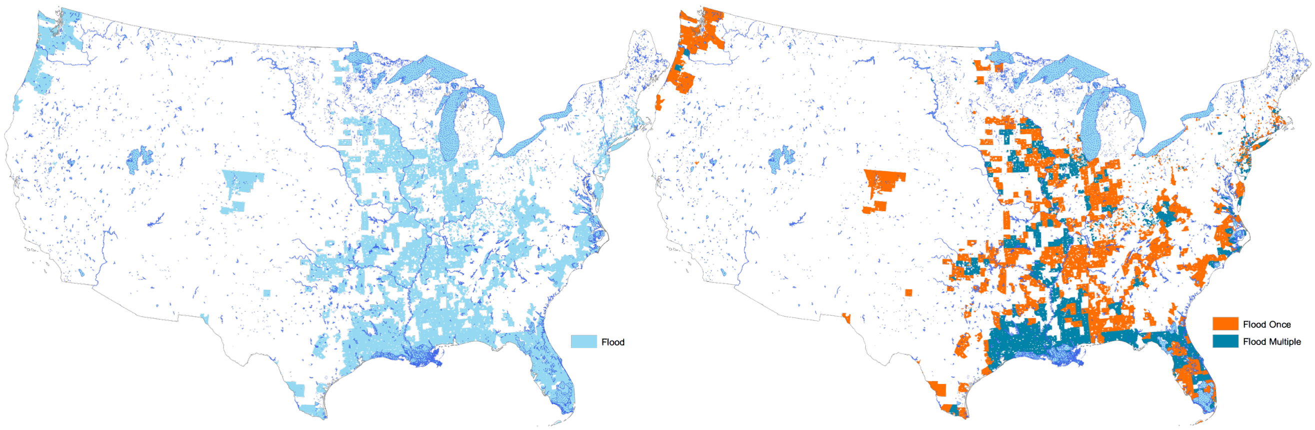

Figure 1: Locations with Single and Multiple Floods between 2003–2013

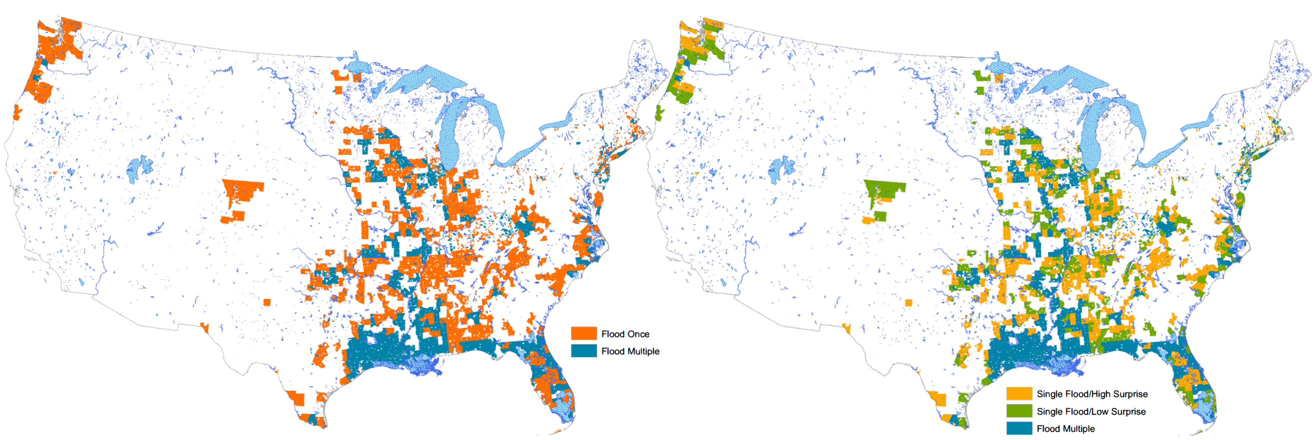

Figure 2: Locations with Flood Surprises between 2003–2013

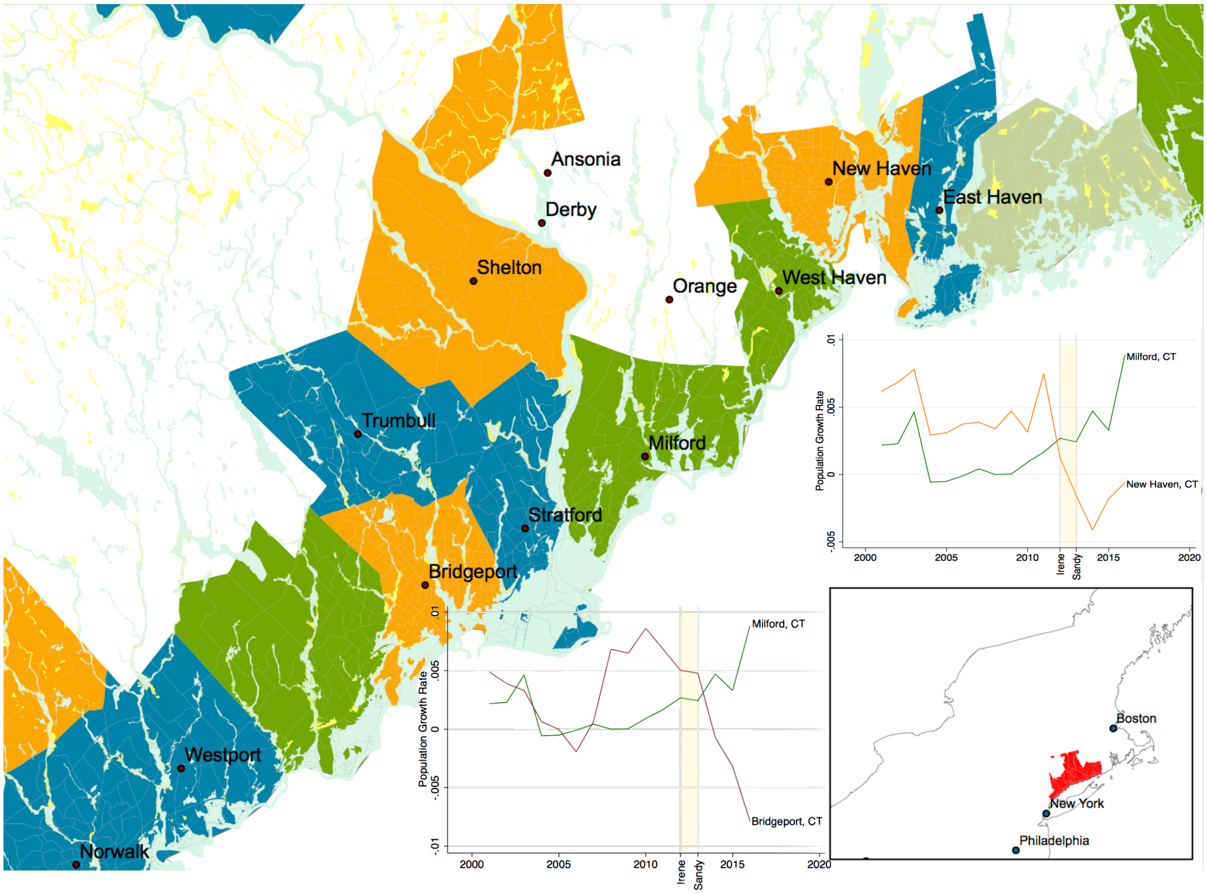

Figure 3: Population Growth of Milford vs New Haven and Bridgeport

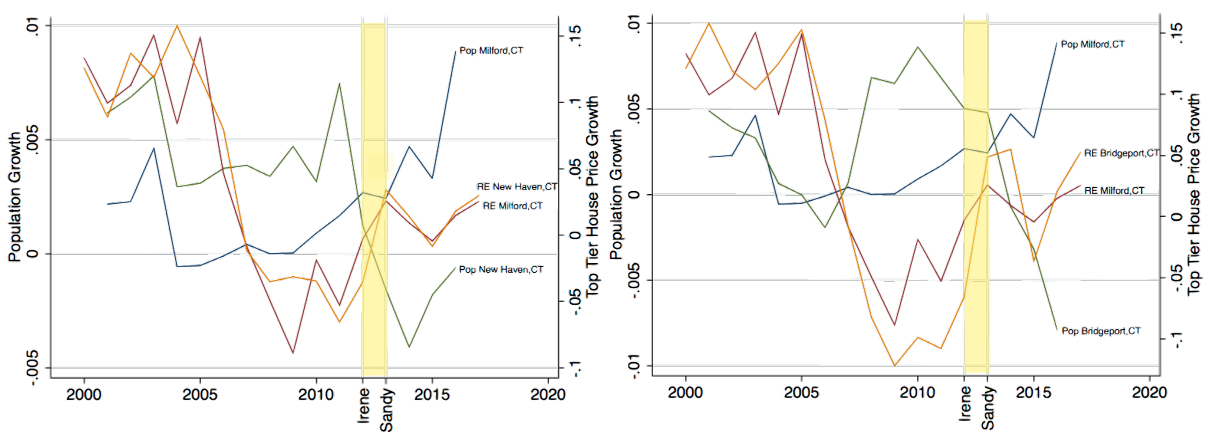

Figure 4: Population and Real Estate Values at Milford vs New Haven and Bridgeport

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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.