Weather Shocks, House Prices, and Population: Role of Expectation Revisions

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Abstract

I document empirical regularities of flooding in the US with newly-compiled insured, uninsured, historical loss, and flood zone data at the town level for the decade after 2003. I identify instances with low damage and low risk expectations, implied by the high uninsured share, where experience with or proximity to flooding can raise perceived risk. I examine the causal impact of flood damage on population change and its interaction with the real estate market. I find that risk revisions are important determinant of population change and real estate values. Only growing places with low historic flood loss or those with low-risk flood planes experience population declines. The decline is related to investments in flood risk mitigation which raise cost of living. Elsewhere, higher risk only depreciates house values, causing higher-income households to leave. Floods also have significant spillovers on population and prices in neighbors with no direct damage.

JEL Classification: R11, R30, J61, Q54

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Real Estate, Natural Disasters

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1 Introduction

Flooding in the US is an important and growing concern, with over 10% of US housing located in a floodplain and population in hazardous areas within the floodplain (1 in 50 year) projected to double by 2050.[1] Even if residents avoid risky areas with historical flood losses and flood zones, changes in the severity of weather or new construction can cause out-of-pocket losses in unexpected locations.[2] Experience with or proximity to such losses can raise risk expectations and cause residents to buy flood insurance, pay for flooding mitigation, or relocate. Identifying how much people engage in each of the three as risk expectations increase is key to understanding how newly impacted communities change over time. Isolating the role of risk revisions is challenging, particularly in the case of extreme-loss events, as housing reductions, job losses, and existing flood insurance also play a role.[3]

This paper studies the causal impact of flooding on population change and its interaction with the real estate market. I focus on communities which experience relatively low flood loss and which have lower insurance coverage as a result of their limited historical experience with flooding. The limited loss minimizes the importance of changes in the supply of houses or employment, among other important factors, while the lower insurance coverage suggests that flooding is unexpected, at least for a portion of the residents. Both imply that the revision of risk in affected communities plays a key role. Gallagher (2014) and Lindell and Hwang (2008) argue that experience with and proximity to flooding lead to risk revisions.[4] In this paper, I posit that the pre-existing level of risk expectations is also important and that revisions in communities with low level of expectations are more likely to affect population and house prices. I identify pre-existing expectations with a new measure of historic loss[5], which relies on new data of housing units completely destroyed by floods since 1978, and

[1]Wing et al. (2018) estiamtes that 15.4 million houses are situated in a 1 in 100 year floodplain.

[2]As of 2011 only 32.5% of the maps "adequately identified the level of flood risk", OIG (2017).

[3]See Landry et al. (2007), Bleemer and van Der Klaauw (2017), and Vigdor (2008) which focus on Katrina.

[4]Gallagher (2014) shows that flood insurance purchases increase after flooding. Lindell and Hwang (2008) highlights previous experience as key to in increases risk perception, while Peacock et al. (2005) report that proximity is important. Shaw and Baker (2010) show that the effect of past experience varies over time.

[5]Main results are similar when I identify lower expected risk with flood insurance coverage instead.

with the size of low-risk flood zones (1 in 500 year).

I use a new dataset of insured and uninsured, town-level flood damage for the decade after 2003, which allows me to distinguish communities with flood losses and those where losses were not expected.[6] I define floods as instances where more than 0.01% of the local real estate value is lost.[7] This definition reveals three important regularities relevant for the empirical design. I find that locations that lose at least 0.01% of real estate value to flooding more than once during the sample period, experience more destructive events.[8] Focusing on places that flood once limits the overall distribution of flood loss for the areas of interest: $90^{th}/95^{th}$ percentiles are 0.46%/1.03% for the single-flood versus 0.86%/1.72% for triple-flood locations. I show that places that flood once during the sample period and have low historical loss (below the state median) also have lower flood insurance coverage – and likely lower flood expectations – relative to those with higher historical loss. This allows me to compare the differences in population and real estate values for areas with lower overall loss but with varying flood-risk expectations, attributing them to the revisions of expectations. Furthermore, by separating communities based on their pre-existing population growth, I can identify whether productivity or amenity factors that attract new residents interact with the baseline effect of expectations on population and real estate values.

I estimate an event-study model identified by shifts in the population average and trend, focusing on places with a single flood during the sample. I test for population changes during/after the flood as well as breaks in the existing population trends. The model controls for fixed effects and pre-flood trends since the communities in the sample are quite different and grow at different rates. I also control for population responses to floods that can

[6]Information comes from FEMA and SBA and includes historical payouts and structures destroyed since 1978, for events at 4,147 census-designated places.

[7]The cutoff is the median value when absolute damage is over \$10,000. This cutoff is arguably arbitrary. Lower values will designate as floods instances where a limited fraction of households are affected, while higher values focus on relatively bigger events. To make sure that I capture cases where poor/vulnerable neighborhoods are affected, I further report results when floods are defined above 0.0076% – the median value for instances with more than \$1,000 in absolute damage.

[8]This finding is also confirmed by Kousky and Michel-Kerjan (2017) with property-level insurance claims data. Note that I include communities with two consecutive floods in the single-flood category.

be explained by local characteristics such as the fraction of renters and non-construction jobs, among others, since these also affect how population changes after flooding. Whether communities are affected at all is an open question. They can just increase flood insurance demand, as shown by Gallagher (2014), or invest in flood mitigation, as in McCoy and Zhao (2018). Furthermore, lower, uninsured damages can be absorbed and floods be ignored as rare events, particularly if expected future severity is low.

I have four main findings. First, single-flood places with low historic loss or extensive low-risk flood zones have lower flood insurance coverage (flood insurance payouts per capita) relative to single-flood, high-historic loss places for the same level of damage. This establishes that low-historic-loss communities likely have lower flood-risk expectations and underinsure against flooding. Second, I find that floods cause a sizable population decline primarily in the low-historic-loss areas. This suggests that uninsured losses and flood proximity – as opposed to the magnitude of damage, which I control for – change expectations of future losses sufficiently and affect the location choice of residents. Third, after separating places with flood-driven population responses by pre-flood population growth, I find that the decline is limited to growing locations. It appears that newcomers steer away from locations with increased flood risk. Fourth, I show that risk revisions spill to no-damage neighbors and cause population there to decline as well.

To understand the mechanism behind revisions of risk expectations, I focus on the real estate market. Higher expected risk can lead to insurance purchases and flood mitigation. The joint population and housing response helps me answer two questions. First, how important is local flood mitigation in growing places as a factor behind the sharp population decline? Insuring higher-value structures is expensive[9] and incentivizes owners to improve flood-resistance. This is reflected in the adjustment of prices and inversely affects population. Second, are uninsured losses ignored in low-growth places, given the lack of population impact? Compensating price declines can explain why population is constant even as expec-

[9]Standard flood insurance has an upper coverage limit of $250,000. Additional coverage can be purchased at a higher cost.

tation are revised.

I show evidence that uninsured losses in growing places lead to housing improvements.[10] Prices remain constant and in half of the US regions they increase even with population declines. The implied improvement is confirmed by the increase in remodeling businesses. Their number is above what is predicted by damages, and has a positive trend break after flooding. Improvements reduce insurance cost and maintain value, but they also require big expenditures from household's wealth or government loans, which can increase cost of living in the community and make new construction expensive. I find that improvements are limited in low-growth places and prices decline significantly. Low housing demand and stable supply allow small population changes to result in big price adjustments, leaving the community size unchanged.[11] The drop in high-tier, quality-adjusted house prices suggests that high-income individuals leave.[12] There is evidence that unoccupied houses are used, instead of flood mitigation, to lower expected risk. The identified responses assume that households can leave. Residents in low-growth areas may experience a lock-in if house values cannot cover the down payment and transactions costs of an outside house, as in Stein (1995). I find evidence of this is some communities within the country.

Population declines in locations with bigger low-risk flood zones. This provides evidence that revisions can occur where historic loss is higher if there are areas with low-risk exposure in the proximity. Both population and real estate prices decline, suggesting a limited improvement in the housing stock and a real estate market that does not fully compensate for higher risk. These communities lose low-income individuals since low-tier housing falls more. Interestingly, places with a bigger flood zone but with no direct impact experience similar effects, emphasizing the role of expectations of future loss.

I extend the baseline result of the paper in several ways. I evaluate the importance

[10] This effect is also confirmed by McCoy and Zhao (2018) in the case of Hurricane Sandy for New York City.

[11] This is a classic result first discussed by Glaeser and Gyourko (2005).

[12] Real estate values a provided by Zillow. They are quality adjusted, which allows me to interpret the price changes as resulting from shifts in demand rather than due to differential flood damage.

of local social capital, measured by the number of social organizations and churches, and find that it minimizes the negative impact on population. I add controls for local land regulation and income and show that higher values of each exacerbate declines in population. I provide disaggregated, regional evidence about the main population and real estate results and confirm that flood surprises have a similar effect across the country.

The evidence is important in evaluating the effect of climate change. I show that places with low past exposure to flooding or those with higher footprint in low-risk flood zones can experience significant population and real estate changes even with minimal actual flood loss. Increased flood-risk expectations will make high-population growth places less dependent on insurance, more expensive, and relatively smaller. Higher value of real estate generates local tax revenues that can be used to further mitigate risk. Locations with lower population growth may be less able to deal with future damages since they experience reduced house values, which lowers local tax revenue and prevention budget, and attract lower-income households. These places will depend more on insurance given the limited house improvements. Places with high historic losses or frequency of flooding do not experience high uninsured losses and maintain stable expectations. Losses are reimbursed through insurances with population and house values unaffected. Areas with bigger low-risk flood zones are an intermediate case. Higher risk makes them smaller but also less expensive.

The evidence shows that places with less than the state-median house units lost to flooding from 1978 to 2003 anticipate close to 20% less damages, when comparing two communities with the same damages but different past loss-exposure. They have 7% more *uninsured* damages as a fraction of their real estate value, compared to high-historic-loss places. Communities with 10% higher share of housing in the 500-year floodplain receive 6% less insurance payments, when comparing to communities with the same flood damage.

Population declines where historic loss is low or 500-year flood zone is bigger. The long-term effect is consistent with the interpretation that expected risk has increased. Controlling for a fixed effect and linear trend, population in the year of the surprise declines by 0.3%, remains 0.5%/0.2% below pre-flood level/trend.[13] Allowing for relative damage, flood-zone size, government relief, and factors which can temporarily confound the population effects, the impact increases: 0.9% initial drop and 0.8%/0.4% below the pre-flood level/trend. The trend decline lowers population by 2%/4.1% in 5/10 years. 10% higher 500-year zone housing decreases population by 0.4% and keeps it 0.8% below the pre-flood level. The effects remain if I proxy for anticipation using 0.1% lost structures or with insurance coverage; the results are also robust to lowering the cutoff definition on floods to 0.0075% of house value.

The decline is only significant in growing places: population drops 1.1% on impact, remains 0.8%/0.55% below the pre-flood average/trend, reducing growth by a third. These locations reach their pre-flood size in two years but population grows slower. Locations with 10% higher low-risk flood zone experience house price declines of 1.6%-2%. The impact of higher risk in the non-growing communities is concentrated in the residential market: housing values drop by close to 5%. The high/mid-tier, quality-adjusted house prices decline by 2.6% suggesting that higher-income individuals leave. There is no change in residential values in high pre-growth place and the number of remodeling businesses increase by 3.7% and continue to increase by 3.6% annually.

In Section 2, I discuss related literature and contributions. Section 3 details the compilation of the data. Section 4 presents the empirical features of flooding. Section 5 includes main results. Section 6 and 7 examine flood spillovers, and extensions/robustness.

2 Related Literature

This paper extends the literature on expectation formation and learning after rare events. I build on Gallagher (2014), which shows that flood insurance demand increases after flooding and reverts to past levels over time, arguing that a learning model with newly arriving residents, not familiar with past flooding, can explain the transient nature of insurance

[13] The main results are based on low-damage events since each specification controls for relative damage, centered at 0.1%. The $95^{th}/97^{th}/98^{th}$ percentiles are 1%, 1.9%, and 2.9% of house value.

purchases. My paper takes as given that experience with flooding raises risk expectations and flood insurance demand. Instead of focusing on purchase of new flood insurance, I examine if increased expectations are strong enough to affect the size of the community and real estate values over time.[14] I extend Gallagher (2014) by showing that the *level* of existing risk expectations varies with the amount of historical losses. I show that risk revisions affect population and real estate values in communities with lower historic flood loss and lower risk expectations. I further differ from Gallagher (2014) by using a more comprehensive measure of flood loss which includes insured and uninsured damage. This is key as it allows me to focus on a subset of communities with non-repetitive, low-scale flood loss (see Kousky and Michel-Kerjan (2017)), which is likely unexpected by a portion of residents.[15] Historical experience with flood loss is also highlighted by Lindell and Hwang (2008); Peacock et al. (2005); Shaw and Baker (2010). Recent work by Kousky (2017) emphasizes that insurance is compulsory for recipients of government relief and can explain some of the increases in coverage after events. My evidence suggests that both insurance coverage and historical damage can proxy for the existing level of risk expectations.

Since a big portion of the flood instances in my paper are related to coastal storms and hurricanes, the results are also related to the literature on natural disasters and their effect on population and housing. A portion of evidence on population comes from hurricanes with extensive damage, not restricted to flooding. Strobl (2011) studies coastal counties during hurricanes during 1970-2005 and finds evidence of only compositional population changes, suggesting that high-wealth individuals leave affected areas. Boustan et al. (2012) estimate the odds ratio of living in or moving to areas which experience different types of natural disasters in the 1920s and 1930s, finding that floods do not dissuade newcomers or current

[14]Note that the size of the community and the number of insurance policies can evolve in opposite ways. Gallagher (2014) compares insurance purchases for growing and contracting communities and finds no difference.

[15]Note that Gallagher (2014) covers the 1990-2007 period, while I study 2003 to 2013. Gallagher (2014) identifies flooding using public-property loss and I use total insured and uninsured loss, counting as flooding cases with more than 0.01% real estate loss.

residents.[16] Boustan et al. (2017) study different types of natural disasters, 70% of which are floods and tornadoes, between 1920 and 2010, defining a disaster as having at least 25 fatalities. This paper finds a positive effect of floods on the migration rate (negative after 1980) and suggests that new public infrastructure is a key factor. Deryugina (2017) studies hurricanes between 1979 and 2010 and finds that population is not affected. Compared to my paper, each of these studies focuses on large-scale events with significant damage. The response of population captures the combined effect of changes in supply of employment, housing, public wealth transfers, among others. My paper differ substantially because I examine a set of communities with minimal damage, where changes in expectations play a significantly bigger role. I add to the existing results in this literature by showing that natural disasters affect population in communities far outside the path of destruction. I also show that the pre-existing risk expectations play a critical role for how population responds to losses. The existing literature does not separately identify the role of expectations.

In the case of real estate, Bin and Polasky (2004) and Hallstrom and Smith (2005) find that hurricanes generally reduce real estate prices in the flood plane; Murphy and Strobl (2010) find that coastal cities see increases in house values after hurricanes. Bakkensen and Barrage (2017) emphasize that heterogeneity in flood risk expectations of homeowners can limit house price responses to increased flood risk. Bosker et al. (2018) use parcel-level house price data for the Netherlands and find that flood-risk reduces house prices.[17] My paper differs from this literature by explicitly considering the impact of pre-existing flood-risk expectations as well as the role of population change following risk revisions. Furthermore, I restrict my results to cases with relatively low damages, suggesting that results are mostly driven by changes in expectations, as in Bernstein et al. (2019) and Atreya and Ferreira (2015). Contrary to the literature, which on average finds that prices decline after floods, I show that housing values can increase. I find that this is related to the pre-existing population

[16]The authors interpret this effect as an outcome to public effort to mitigate against flooding.

[17]Gibson et al. (2017) use disaggregated housing data for New York City and find that signals of higher flood risk reduce house prices. Indaco et al. (2019) also uses parcel-level data and finds that inclusion in the floodplain reduces house prices.

growth and investments in flood mitigation. House investments which mitigate flooding are discussed in McCoy and Zhao (2018). I also show that house prices can decline in cases where housing is widely available but flood risk increases.

Finally, the paper is also related to studies, reviewed by Rosenthal and Ross (2015), which examine the effect of environmental risk on population and housing. A select set includes Davis (2004), Banzhaf and Walsh (2008), and Kahn (2000). 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. Relative to this literature, I emphasize that current economic conditions, e.g. current population growth, can affect how revisions of risk will impact the housing market and the size of the community. I further show that newcomers choose to go to communities that do not experience increased flood risk and that local residents invest in flood mitigation. Both represent adaptations to higher expected risk, which are key in projecting the impact of climate change, as in Desmet and Rossi-Hansberg (2015).[18]

3 Dataset and Institutional Details

Flood Insurance: 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 – with flood-zone designations and enforcement. The map delineates Special Flood Hazard Areas (SFHA) with varying degrees of flood risk. The 100-year and 500-year flood zones represent two general categories of flood risk in the SFHA. Flood is expected to occur in each 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

[18] For an example of adaptation to flooding in big cities, see Kocornik-Mina et al. (2015).

otherwise.[19] Premiums of flood insurance vary depending on the designation of the flood zone and the elevation of the structure. The yearly premium for a structure within the 100-year zone is about \$6,000 to \$10,000 depending on the extent of direct water exposure and deductible. Total amount of coverage is set at \$250,000 for the structure and \$100,000 for belongings. In order to get additional coverage, homeowners will need to buy additional insurance, which is generally more expensive.

Data Sources: The amount of insured damage comes from reimbursements data by the NFIP for incorporated area. FEMA, the administrator of flood insurance, provides on its website a running total of payments to each community and total destroyed structures since 1978. I use archived views of this list in order to get a snapshot of total payments and their change at regular periods within each year between 2003 and 2013. The change in payments represents total disbursements to cover insured loss each year. I use the list of disaster declarations provided by FEMA in order to identify counties which experience uninsured flood losses in a given year and associate to them insurance payments for that year. The insured damage is matched to the set of disaster declarations in a given year in a given county which, in turn, are associated to uninsured damages.[20] The data includes limited information on the number of policies and total coverage for a subset of years. I take advantage of this data when comparing historical losses to insurance purchase. Note that while disaster declarations represent cases with bigger damages, these are not uniform across locations and the main results focus only of low-damage events.

The uninsured loss information comes from the FEMA/Small Business Administration (SBA) information. FEMA and SBA are the two agencies in charge of relief for households who experience uninsured damage within disaster declaration communities. FEMA administers non-refundable aid, while SBA provides low-interest loans. In each case, inspectors will survey the affected households and will record total damages at the premise. I use this estimate to quantify total uninsured damages, as opposed to total loans or relief payments

[19]Kousky (2018) provides an in-depth discussion of the NFIP.
[20]75% of community/year cases feature total losses based on insured and uninsured damage.

which have a cap by law. FEMA also administers relief funds for local public infrastructure. I include the estimated damages on public property.

The sample covers the 38 US states which include flood-related disaster declarations. Table 1 lists the states and the number of communities which are affected. 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. Total damage comprises four components: insured individual/business from NFIP; uninsured individual from FEMA and SBA; uninsured business from SBA; uninsured public from FEMA. I use the components to control for events where most of the damage comes from one of the source. Appendix A1 has additional information.

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. I combine locations with less than fifteen thousand people with the county unincorporated areas to make sure that results are not driven by very small settlements. Real estate information comes from Zillow and is available at the zip-code level. It provides quality-adjusted 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. Following Banzhaf and Walsh (2008), I convert the zip-code information to the level of the community by using census-block-based population weight for each zip code. Similarly, I convert flood-zone maps into census blocks by overlaying the two using GIS. The rest of the information used in this paper comes from the 2000 US Census data at the block-group level. I also use the County Business Patterns for establishment data and the USPS dataset for mail service.

Definition of Floods and Flood Surprises: I identify floods according to the relative size of the damages: cases where more than 0.01% of the total local real estate value is destroyed constitute a flood. The relative damage distribution in the sample is very asymmetric: the $95^{th}/97^{th}/98^{th}$ percentiles are 1%, 1.9%, and 2.9% of house value. I use 0.01% as a cutoff since it is the median for events with at least $10,000 in absolute flood loss. There are two reasons to set a relatively low cutoff. First, I focus on a wide spectrum of events because relative damage is context specific – less destructive floods can impact perceived risk if they are surprises. Second, insured households will likely be reimbursed for losses, while the uninsured will not always borrow from the SBA or contact FEMA to cover some of the losses. As a result, uninsured damages may be underestimated. I set a low cutoff in order to avoid excluding communities which experience a flood but have low coverage since these are more likely to revise risk expectations.

There are two ways to proxy for risk expectations: with insurance purchases or with historical losses. I verify that results are consistent when using both. Each measure has drawbacks. Insurance purchase is required in the 100-year zone or if a household has received government aid. As a result, households can be required to have insurance despite their low expectations. While the enforcement of this requirement is not uniform, it is more likely to indicate that expectations are high in locations with recent floods where government aid is conditional of insurance purchase. On the other hand, historical losses will not account for any changes in the local protection infrastructure which can minimize future risk. Since historical losses are more likely to cause insurance purchases directly, or indirectly through changes in the flood zones, I identify surprises using previous damage and flood zones.

I measure of historic damage with the total structures completely destroyed due to flooding between 1978 and 2003, provided in the FEMA data of insurance payments.[21] I further normalize it by the total building structures in 2000 and compare to the state median across all location that experience a flood. Communities below the median are considered low-risk and assumed to experience flood surprises. Using the median ensures that the distinction between high and low surprise is region specific and that there are sufficient number of places which can be placed within each category. In the robustness section, I assume that high surprise are only communities with less than 0.1% lost structures or where the active policies

[21]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.

are less than 25% of the number based on the population located in the 100-year zone.

4 Empirical Regularities of Flooding in the US

One of the goals of this paper is to describe the US experience with flooding, caused by both hurricanes/coastal storms and rain/snowmelt in landlocked areas, in the decade after 2003 with a carefully compiled and consistent measure of total damage based on insured and uninsured damage for each incorporated area. To my knowledge, this is the first nation-wide characterization of insured and uninsured flood loss, as the literature either works with high-quality, disaggregated information for small-area studies or uses proxies for damage, such as disaster declarations, in large-scale ones. Total damage is scaled by real estate value to allow comparisons across locations. I define a flood as an instance where more than 0.01% of the local real estate value is destroyed. This number is arguably arbitrary and represents the median value for all events with more than $10,000 of absolute damage. Using a higher cutoff will exclude many smaller events and focus on bigger floods. A smaller cutoff can lead to identification based on local factors not related to flooding. The data includes hurricanes and wide-scale flooding since both generate significant damage by flooding. While the empirical regularities here are based on 0.01% cutoff, I show that the main results in the paper hold with a 0.0075% cutoff.[22]

There are several important features that emerge when comparing the national flood experience during the ten years after 2003. These are based on the summary statistics in Table 1 and Table 2 and Figures 1 through 3.[23]

First, I document that there is a substantial variation in the extensive margin at the national level and across states. A substantial number of communities lose at least 0.01% of real estate value more than once in the sample. Figure 1 shows that flooding is widespread

[22] 0.0075% is the median relative damage for events with more than $1,000 of aboslute damage.

[23] Note that communities that are flooded twice in two years are considered single-flood. This choice is guided by the event-study empirical model in the paper and the consideration that two consecutive hurricanes are very unusual.

across the country and that communities with multiple floods are not located only at the coast.[24] In the interior, major floods result from significant rain or snowmelt which causes rivers and creeks to spill in the surrounding areas. Table 1 shows that out of the total 4,147 communities in the data, 36%/13%/7.6% experience one/two/three-plus floods during the sample decade. Flooding is a frequent concern nationwide, not just a problem associated with infrequent hurricanes. The frequent-flooded locations are not clustered, they are in 17 of the 38 states. The list of states and number of communities in each can be found in Table 2 in the Online Appendix. While most of these states have ocean exposure, several land-locked states contain frequently flooding communities. Seven states contain only single-flood locations.

Second, I find that locations that lose at least 0.01% of real estate value more frequently during the sample on average tend to experience more destructive events. In other words, the extensive margin is positively related to the intensive margin and is associated with other community differences consistent with higher expected risk.[25] This is contrary to the intuition that locations which deal with flooding events more frequently can protect against bigger damages. In Table 1, relative damage increases when comparing communities with one/two/three and more floods along each of the reported percentiles. Differences in the 95^{th} percentile are particularly pronounced: 1% for single flood to 1.6% for two floods and 8.7% for four floods. Relative damage differences are also evident when using absolute damages as in the second panel of Table 1. In the first panel of Table 2, we also see that historical losses and insurance increase with the frequency, showing that location differences are persistent and are reflected in current expectations. House price differences exist mostly when comparing locations with and without floods, with the latter being more expensive.

Third, I show that one-flood locations tend to share a border with communities that flood more frequently: 66% are next to at least one multiple-flood place. This can be seen

[24]Gallagher (2014) already shows that flooding is widespread, using just presidential declarations. I provide evidence that many communities flood several times in the sample. This is highlighted by Kocornik-Mina et al. (2015) for cities in general.

[25]This is confirmed by Kousky and Michel-Kerjan (2017).

in Figure 1. Of those, 64% have low historical loss, suggesting that more significant events from outside can generate flood surprises. Single-flood places are also close to areas with one flood but with high historical loss (above median housing units destroyed by flooding as a fraction of total local units), which can be another source of surprise flooding. High-historic-loss communities are shown in Figure 1 as "low surprise." They tend to be contiguous to multiple-flood areas, which reinforces the assumption that the former are at a generally higher risk of flooding.

Fourth, there is a significant difference in flood insurance coverage among locations with one 0.01% real estate flood loss during the sample period based on their historical loss experience, i.e. the number of housing units lost to flooding since 1978. The second panel of Table 2 divides single-flood communities relative to the state median of housing units lost to flooding (as a fraction of total local units): HistLoss^- includes communities with less than the state median, while HistLoss^+ includes those above. The panel shows that communities with below median losses in the state distribution have 14 insurance policies per thousand people as opposed to 53 for the rest. After a flood, the former reimburse 18.8% of damages as opposed to 27.8%. High-historic-loss communities have a higher fraction of population in flood zones. This suggests that historical loss can lead to changes in local zoning which can lead to higher insurance purchases. 2.7% of low-loss communities live in a 500-year zone where insurance purchase is not mandatory. This part of the location is more likely to revise expectations after a flood.

Fifth, I find that population growth is higher in communities with higher exposure to water as long as expected risk, proxied by historical loss experience, is lower. Figure 2 provides scatter-bin plots of a subset of the dataset in the paper. The first panel of Figure 2 shows that higher fraction of housing in the 100 and 500-year flood plane is associated with higher population growth for the community between 2000 and 2005. The second panel of Figure 2 shows that this is driven by places with lower historical loss (the HistLoss^- group described above). The regression coefficients from the second panel imply that a10% increase in flood-plane housing is related to 2.5% higher growth. Table 2 shows that population increases in locations that appear safer from a historical-loss perspective and where housing provides significant water-based amenities. This is further confirmed by the difference in relative house values. Figure 3 presents visual evidence for the Top-tier Housing and shows that housing is more expensive when its close to water and where historical losses are low. This suggests that population is guided both by the relative flood risk captured by historic exposure and by the local amenities.

5 Main Results

The main results examine the role of new risk information from underinsured events in the location choice of locals and newcomers. I show that past damage and low-risk flood zones are useful as a proxy for flooding with higher fraction of uninsured damages and lower expected flood risk. I interpret these events as flood surprises that increase expected risk, examine their effect on the average community, and characterize the role of existing growth. I explore the underlying mechanism with evidence from the housing market.

Historical Exposure, Flood Zones, and Insurance in the Cross-section

Homeowners have discretion about whether to buy insurance or, if purchase is required, what deductible to set. Lindell and Hwang (2008) show this decision is related to expectations, suggesting that low reimbursements indicate low expectations. Places with low past losses and low-risk flood zones have limited flood experience and can exhibit low expectations.[26] I examine the extent to which they can explain instances with lower reimbursements, after controlling for damage, by comparing insurance payouts by historical loss and flood zones in

[26] Lindell and Hwang (2008) show that previous experience increases flood risk perception, while Peacock et al. (2005) report that proximity is important. Shaw and Baker (2010) show that the effect of past experience can change over time.

the cross-section of all events, i.e. using only instances of floods:

$$\begin{aligned} Y_i = \beta_s \mathbb{1}(1Flood_i) + \gamma_s Damage_i + \delta_s HistLoss_i^+ + \eta_s Damage_i HistLoss_i^+ + \\ \psi_s Sh500YearZone_i + \alpha_s Damage_i Sh500YearZone_i + \sigma_s X_i + \zeta_{\bar{s}} Z_i + \gamma_{s\times t} \ + \epsilon_i \end{aligned} \tag{1}$$

Y_i is log of flood insurance reimbursement, share of insured damages, or policies per capita in community i with a flood. $\mathbb{1}(1Flood_i)$ and $HistLoss_i^+$ are indicators for single-flood community and above-median historical loss. $Damage_i$ is log of total damage per capita, or relative damage in the case when regressed on share of insured damages. $Sh500YearZone_i$ is the share of housing in the 500-year flood zone. Coefficients vary by flood frequency with s indexing single-flood locations. X_i includes interactions of flood indicators with the fraction of housing in the 100-year flood zone and the shares of different types of damage.[27] Z_i includes flood indicators and damage controls for multiple-flood places. Finally, $\gamma_{s\times t}$ is a state-year fixed effect which ensures that identified coefficients are based on within state-year differences.

Anticipated damages result in reimbursements which track observed loss. I examine whether the deviations between the two can be explained by historic flood experience or low-risk flood zones. A positive δ_s implies that a high-historic-loss location anticipates a bigger proportion of damages for any level of losses. A positive η_s indicates that for places with high-historic loss the higher the damage the higher the insurance payments. A negative ψ_s suggests that bigger low-risk zones have low risk expectations, insure less, and have lower reimbursements for the same level of damage. A negative α_s suggests that with higher-damage events, communities with bigger 500-year flood zones receive less insurance. It is important to control for high-risk (100-year) flood zones because historic damages can update zoning and require insurance purchase from more residents, explaining why past losses lead to higher coverage. This implies that the effect of high historic loss identifies risk expectations

[27]FEMA and SBA damage control for incidence on low-income/higher-income households. Uninsured damage not covered as a loan by SBA is provided as a non-refundable relief by FEMA.

distinct from flood zoning.

Table 3 shows estimates from model (1). The results suggest that less flood insurance is purchased in low-historic-loss places. In column (1), we see that increases in damage per person are associated with higher flood insurance payouts. Despite this, historic experience still plays a role in explaining insurance payments: the average high-historic-loss location has 79% higher payouts compared to low-historic-loss places, at any level of current damage. This can be driven by high-historic-loss communities being affected by bigger, more damaging storms. Column (2) allows the effect of historic experience to vary with actual flood damages, which can test whether historic experience matters at low and at higher damage levels. The results show that low-historic-loss places anticipate close to 20% less damages, when comparing two communities with the same damages but different past experience. The higher uninsured losses are indicative of lower expectations and can lead to significant revisions of risk.[28] In column (3), we see that low-historic-loss places have 7% more *uninsured* damages as a fraction of their real estate value, compared to high-historic-loss places. This insurance difference does not appear to vary with the size of the relative damage, as seen in column (4), which interacts historic damage with current relative damage. The effect of the share of housing in the 500-year zone is significant in column (2), but not in column (1). In the former, we see that comparing two communities with the same damage, the place with 10% higher share of 500-year housing receives 6% less insurance payments. In column (4), the 500-year share is only significant when interacted with relative damage, suggesting that in this model the effect of each cannot be identified separately. The results for the 500-year share provide a somewhat mixed support for identifying areas where uninsured losses from low-impact events can lead to revisions of expected risk.

Columns (5)-(6) provide estimates using limited data on insurance purchase before a flood. The number of policies is available only for 2005, 2006, and 2010 floods. This is sufficient to estimate differences in policies only for single-flood places. The evidence, both with

[28] I also verify that the main results are preserved when using insurance coverage instead of historic loss.

and without damage interactions shows that the high-historic-loss places have significantly more flood insurance policies per person compared the low-historic-loss places. Places with past losses have almost three times the number of insurance policies per person. The effect of the share of 500-year flood zone housing is also positive and significant, implying a sizable difference in flood insurance policies with bigger flood zones. While the results are based on a much smaller dataset, they are consistent with the reimbursement evidence and show that low-historic-loss places and those with bigger 500-year flood zones are more likely to be subject to unanticipated, low-impact floods. The effect of flood zones implies that residents take the zoning information into account. Higher flood zones are related to more policies. Reimbursements in the 500-year zone are relatively lower, at least in column (2), because higher purchases do no imply that everyone at risk buys insurance.

Overall, the results confirm that differences in historical flood experience and 500-year flood zones explain how damages are anticipated. Both independently are associated with lower insurance for a given level of damage. They identify instances where expectations are low and the experience or proximity to flooding can lead to revisions. As a robustness check, I also identify unanticipated floods using relative insurance coverage as a robustness check.

Population Response to Flood Surprises

Here, I quantify the extent to which flood events provide new information which not only leads to revisions of risk expectations but also is sufficient to affect the location choice of local population and potential newcomers. I account for invariant differences in location averages and linear trends, as well as differential responses conditional on local characteristics:

$$\ln Pop_{ist} = \beta_s \mathbb{1}(t = Flood_i) + \sigma_s \mathbb{1}(t > Flood_i) + \phi_s t \mathbb{1}(t > Flood_i) + \delta_s X_{it} + \zeta Z_{it} + \alpha_i + \psi_i t + \gamma_{s\times t} + \epsilon_{ist} \tag{2}$$

Log population for place i within state s in year t is explained by a location average, α_i, linear trend, ψ_i, and a state-year effect, $\gamma_{s\times t}$. The specification allows for time-invariant differences in location size and growth, and identifies the effect of floods by common deviation from each community's average and trend.[29] β_s is the effect within the flood year; σ_s captures the persistence; ϕ_s allows for a pre-flood trend break. X_{it} includes interactions of $\mathbb{1}(t = Flood_i)$, $\mathbb{1}(t > Flood_i)$, and $t\mathbb{1}(t > Flood_i)$ with relative damage, centered at 0.1%, the fraction of housing in the 500-year flood zone, and the fraction of FEMA damages. The first interaction implies that β_s, σ_s, and ϕ_s are population effects for locations with low-impact flooding. The second interaction is of particular interest since it captures the effect of underinsured losses due to low-risk flood zones. The third interaction controls for areas where more of the affected are low-income households. I explore this effect further in the extensions section. I also include interactions with the the share of construction employment, renters (each centered at their median) and insured/business damages.[30] Z_{it} includes indicators for periods and trends before/during/after for multiple-flood places. Finally, the state-year effect captures state-driven variations in local population.

The Census-based construction and renters shares are time-invariant and only allow to identify if locations with more construction workers and renters respond differently. This is critical since single-flood places border multiple-flood ones and serve as a destination for the displaced and temporary workers. Low construction share implies a higher availability of job opportunities outside construction which draws in displaced population; a high share leads to an outflow of construction workers who help repairs affected areas. The renter share controls for the capacity to accommodate the displaced and emergency/temporary workers.

The specification can account for factors that are commonly viewed as endogenous with respect to the size of flooding. For example, it is possible that an unobservable factor causes communities to invest less in flood protection and ultimately leads to bigger damages. As long as this factor is internalized by the local population and the potential new-comers, it will be reflected in the population trajectory before and after the flood, and will be accounted

[29] Size/trend differences are discussed in Desmet and Henderson (2014) and Desmet and Rappaport (2017).

[30] In the extensions, I include interactions with the level of income, land regulation, local social organization, among others.

for by ψ_i. If the factor is internalized after the flood, it is captured by the X_{it} interactions.

I extend the baseline model by allowing β_s, γ_s, and ϕ_s to differ by historic loss:

$$\begin{aligned}\ln Pop_{ist} = {} & HistLoss^{-}(\beta_s^L \mathbb{1}(t = Flood_i) + \sigma_s^L \mathbb{1}(t > Flood_i) + \phi_s^L t \mathbb{1}(t > Flood_i)) + \\ & HistLoss^{+}(\beta_s^H \mathbb{1}(t = Flood_i) + \sigma_s^H \mathbb{1}(t > Flood_i) + \phi_s^H t \mathbb{1}(t > Flood_i)) + \\ & \delta_s X_{it} + \zeta Z_{it} + \alpha_i + \psi_i t + \gamma_{s \times t} + \epsilon_{ist}\end{aligned} \tag{3}$$

This model distinguishes between the effect of unanticipated and anticipated floods. I use three different measures to proxy for surprise floods. In the baseline results, I use the number of fully destroyed houses during 1978-2003 relative to each town's total housing units. I then calculate to the state median and assign communities to the $HistLoss^{-}$ (low historic loss) category if they are below the median or to $HistLoss^{+}$ (high historic loss) if they are above. I also use 0.1% of local structures destroyed, which applies the same cutoff for the entire country. Lastly, I compare the insurance policies per capita to the fraction of population within the 100-year flood zone. Surprises are assumed to occur in places with active policies less than 25% of the fraction in the 100-year zone.

Finally, I allow coefficients to differ by historical losses and previous population growth:

$$\begin{aligned}\ln Pop_{ist} = {} & HistLoss^{-}HistGr^{-}(\beta_s^{LL} \mathbb{1}(t = Flood_i) + \sigma_s^{LL} \mathbb{1}(t > Flood_i) + \phi_s^{LL} t \mathbb{1}(t > Flood_i)) + \\ & HistLoss^{-}HistGr^{+}(\beta_s^{LH} \mathbb{1}(t = Flood_i) + \sigma_s^{LH} \mathbb{1}(t > Flood_i) + \phi_s^{LH} t \mathbb{1}(t > Flood_i)) + \\ & \delta_s X_{it} + \zeta Z_{it} + \alpha_i + \psi_i t + \gamma_{s \times t} + \epsilon_{ist}\end{aligned} \tag{4}$$

$HistGr^{-}$ is an indicator for communities which did not experience population growth in the period prior to the flood. $HistGr^{+}$ indicates communities with positive growth. Growing locations attract more new-comers and experience demand for new housing because of improved labor market or/and local amenities. Conditioning on pre-growth can reveal how persistent demand for housing and more expensive real estate can affect 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.

Columns (1) and (2) of Table 4 report estimates from model (2) with/without controls. Population in the average single-flood place drops by 0.4%-0.56% after the year of the flood. The contemporaneous effect is only significant with controls.[31] 10% higher fraction of housing in the 500-year zone leads to 0.3% lower population on impact and 0.78% lower population in the period after the flood. Higher relative damage leads to lower population decline since more damaging events are more anticipated. Columns (3) and (4) show results from model (3). Population declines are significant only in communities with lower risk expectations/higher uninsured damages. Column (4) shows that population drops by 0.93% on impact and remains 0.79%/0.37% blow its pre-flood level/trend. The effect of 10% higher 500-year zone implies that population drops by 0.39% on impact and remains 0.83% blow its pre-flood level. The negative effect on population is lower than that from low-historic-loss since expectations in the flood zone are likely higher. Each of the effects is estimated at low relative damages which strongly suggests that these are driven by revisions of expected risk not supply/wealth effects. Locations where expected risk is higher are not affected.

Columns (5) and (6) of Table 4 measure unanticipated floods based on 0.1% historically-destroyed structures and 25% insurance coverage. In the both cases the results are very similar. This is due to the tight link between historical experience and insurance coverage discussed above. Since historical losses lead to higher coverage, one can use either to identify unanticipated floods. 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. I explore these alternatives in the robustness section. The evidence suggests that they are not able to explain why population decreases after a risk revision. Finally, column (7) reports results when floods are defined as losses over 0.0075% of house value. These are very close to the baseline case in column (4). The estimated coefficients are slightly

[31]The effect of construction employment is negative, while renter share is positive.

lower, reflecting the inclusion of communities with lower impact.

Columns (1) and (2) of Table 5 report estimates based on model (4). Declines in population occur only in attractive communities with positive pre-flood growth. Population drops by 0.55%/1.1% without/with controls and remains 0.54%/0.82% lower in the post period. The pre-trend declines by 0.41%/0.55%. These communities experience a drop in population and a slowdown in growth after the flood surprise. Since the average growth in low-loss/high-growth communities is 1.5%, the increase in expected risk reduces growth by a third. The estimates suggest that these locations reach their pre-flood size in two years but continue to growth slower. Using alternative measures of flood surprises does not change the main conclusion: columns (3) and (4) show that only growing communities experience population declines. The insurance-based measure implies somewhat lower responses while the 0.1% cutoff shows higher declines in population.

The short-term declines are much smaller than the impact over the five or ten years following the flood. In attractive locations the medium-term impact is between three and five-times bigger. The relative magnitude supports the interpretation of the flood generating uninsured losses which change risk expectations. A purely supply-driven shock with no change in risk will have the opposite relative magnitude with bigger effect on impact.

The unanticipated floods in attractive communities slow down the pre-flood growth but they continue to expand afterwards. This raises the question of whether local housing compensates for the increased risk or there are additional improvements in local infrastructure which mitigate risk. Similarly, the lack of change in the population of low-growth communities is consistent both with surprises having no risk information or with significant compensation in residential prices. The next section investigates how developments in the real estate market help explain the effect of flood surprises.

Real Estate Responses

The population evidence leaves several unanswered questions related to the mechanism through which growing communities slow down. In principle, the decrease in demand for housing can reduce prices and lead to a relatively small population effect. Alternatively, homeowners can improve housing structures and increase residential prices for existing and new construction, further reducing population. The real estate market can shed light on the relative size of the population adjustment based on the size of response of housing. It also allows us to distinguish whether low-growth communities ignore the information from floods or adjust primarily through price changes.

The main results are based on estimating model (4) using house price information from Zillow for three separate tiers. Coefficient estimates are listed in Table 6. There is no evidence that house values, across all three tiers, compensate for the increase in flood risk at growing locations. This is the case for the baseline measure of unanticipated floods in columns (1)-(3) as well as with the two alternative ones in (4) and (5). The decrease in population and constant residential prices are consistent with subsequent investments in local housing which offset the increase in expected risk and make existing housing and new construction more expensive. I provide evidence for this by examining how businesses engaged in house remodeling (NAICS 236118) change after an unanticipated flood, using information from the County Business Patterns data. The results in column (6) show that high-growth communities see a substantial increase in the number of remodeling businesses. There are 3.7% more establishments during the year of the flood and they continue to increase over time as implied by the 3.6% increase in the post-trend. Note that higher relative damages increases the number of these businesses as communities rebuild. In the case of growing communities, this rebuilding is not due to higher overall damage but due to uninsured losses which lead to revisions of future risk. I further experimented with other construction industries and did not find any significant changes.

The evidence implies that unanticipated floods increase expected risk and incentivize home owners to lower future exposure to damages. Owners save on insurance cost and do not have to provide a compensating discount in the case of future sale. The higher value of housing in growing places can additionally motivates investments as in Gyourko and Saiz (2004). This suggests that in high-growth communities owners effectively experience a one-time wealth loss which preserves the value of their real estate. As a result, existing real estate and new construction are more expensive relative to the existing flood risk which reduces population growth in the community. Capozza and Helsley (1990) suggest that uncertainty due to expected flood risk can delay new construction and increase prices of existing housing.

In the case of low-growth locations, the evidence shows a clear decline of house values after risk revisions. Top and middle-tier housing decrease by 2.7%/2.5% on impact; the dip is persistent and remains 3.7%/4.2% lower in the post period. Bottom-tier housing does not appear to decrease on impact although it declines by 5.3% in the post period. The change in house prices implies that flood surprises provide new risk information in low-growth communities despite the lack of population adjustment. Price adjustments dominate quantity ones because these locations have a bigger stock of available houses due to the lack of pre-existing growth. I provide evidence of this by examining how the stock of houses without mail service changes, based on the USPS dataset which tracks whether an address can receive mail. Evidence in column (7) shows the fraction is higher before the surprise, declines by 0.91% during the impact year, and remains 0.69% lower. Higher damages and more housing in the 500-year zone are associated with a higher number of unoccupied housing. This results for low-growth places show households can move within rather than invest in improving the existing structures. Absent additional home improvements, residential prices will decline. In these communities, the decrease in residential prices is sufficient to offset the increased risk. In fact, there is a notable increase in population growth as seen in Table 5 which can be linked to the decrease in house prices. 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 after disasters.

Locations with a higher fraction of 500-year flood zone housing experience decreases in house prices. 10% higher fraction leads to 1.6% decline in top/middle-tier prices and 2.1% in the bottom tier. There is evidence that the growth of house prices decreases between 0.18% and 0.38% after the flood. The relatively higher drop in bottom-tier housing suggests that lower-income households leave. The fact that both population and house prices decline, suggest that there are some limited house improvements, which are not sufficient to completely offset the depreciation of house prices.

All together, the housing and population results suggest that flooding in places with previous experience does not affect the community because expectations remain stable and damages are insured. In contrast, uninsured, low-level losses cause revisions of flood expectations, which can either lead to the purchase of flood insurance or investment in home improvements. In attractive communities the stock of housing is limited and existing structures are more valuable. This incentivizes homeowners to invest in remodeling to offset increasing risk and maintain real estate values. While residential prices are not affected, the effective cost of living increases resulting in a lower future growth. In less attractive communities, the existing stock of unoccupied housing prevents homeowners from investing in improvements of structures. Instead, they can limit risk exposure by moving within the community. As a result of this population remains constant but residential prices adjust in order to compensate for the increased risk. Low-risk flood zones are an intermediate case with limited house improvement which is not sufficient to offset the decline in housing. Changes in prices do not completely compensate for higher risk and population declines.

6 Flood Spillovers

Expectations of flood risk can be affected in places without direct damage. Lindell and Perry (2000) summarizes evidence of the effect of mass media on personal mitigation behavior. Gallagher (2014) shows that insurance purchases pick up after floods at locations within the same media market. This suggests that flood experience elsewhere can help update local risk expectations. I explore this with a simple extension of the baseline model which allows spillovers in two different set of locations: places in counties without direct effect and those, in affected counties, without direct damage. More specifically, I estimate:

$$\begin{aligned} Y_{ist} = {} & I_{NoFCnty}(\beta_1 I_{t=F_1} + \beta_2 I_{t=F_2} + \beta_3 I_{t=F_3}) + I_{FCnty/NDam}(\bar{\beta}_s I_{t=F_1} + \bar{\sigma}_s I_{t>F_1} + \bar{\phi}_s t I_{t>F_1}) \\ & + I_{FCnty/YDam}(\beta_s I_{t=F_1} + \sigma_s I_{t>F_1} + \phi_s t I_{t>F_1}) + \delta_s X_{it} + \zeta Z_{it} + \alpha_i + \psi_i t + \gamma_{s\times t} + \epsilon_{ist} \end{aligned} \tag{5}$$

where Y_{ist} is either log of population or log of residential prices. $I_{NoFCnty}$ refers to the set of locations in counties with no direct impact. β_1, β_3, and β_3 quantify the effect of being next to a single or multiple-flood county at the time of the event. $I_{FCnty/NoDam}$ refers to the set of locations within directly-affected counties which do not experience direct losses. In this case, I can examine the effect of being a neighbor to a single-flood community and break this down into a contemporaneous effect, $\bar{\beta}_s$, a post- effect, $\bar{\sigma}_s$, and a trend break, $\bar{\phi}_s$. The rest of the model follows the baseline specification.

The evidence, reported in Table 7, confirms that floods can affect places away from the epicenter of damages. In the case of population, column (1) shows that locations outside of flood counties experience effects depending on the frequency of flooding in the neighboring areas. Since higher flood frequency is related to higher average damages, the effect on neighboring counties has a non-linear damage-related impact on local population. For smaller levels of damage population is not affected or can increase. New population avoids places with moderate damage and moves to neighboring counties, which are viewed as a safer alternative. Neighbors to high-frequency flooders are negatively affected, implying that with bigger damages, even neighbors are avoided. Results from columns (2)-(4) show that residential prices are positively related to the identified changes in population. This implies that there are minimal changes in house supply, real estate does not fully compensate for proximity to risk, and shifts in demand primarily explain changes in population and prices.

Locations sharing a county with single-flood communities but are not directly impacted are also affected. Population decreases on impact by 1.4%, remains 1.6% lower in the post period, and the pre-trend declines by 0.32%. The evidence is consistent with the interpretation of unanticipated floods which provide new information about future risk. There are two reasons why the impact can be bigger than for those directly affected. First, business damages can reduce employment for commuting workers from nearby, unaffected locations. Second, the level of expected risk can be even lower in places without a flood, leading to a higher risk revision. Mid/low-tier housing prices decrease on impact by 1.6%/1.1% and remain 1.5%1.8% lower. High-tier housing prices are not affected. This implies that higher income households likely invest in improving their structures and offset the increased risk expectations. Mid-income households do not invest and likely leave, leading to compositional changes. This is also consistent with mid/low income individuals being more likely to commute and be affected by business damages nearby. The effect of low-risk flood zones is similar in the case of areas within affected counties but with no direct damage. Population declines by 0.3% and remains 0.8% below average for places with 10% higher 500-year flood zone share. House prices decline by 1.5%-2%, with the bigger decline for the low-tier housing.

Finally, we see that the estimates for directly affected communities are very similar to the main results in Table 4. Taking all of the spillover evidence together shows that a wide range of areas will be affected by flooding. More importantly, some community experience population and residential-price impacts without a direct exposure to damage. This highlights the importance of disaggregated, detailed loss information as well as the significance of revision of risk expectations. The latter can operate at a longer distance and impact communities far from the focus of the damage.

7 Extensions and Robustness

Regional Results: The main results are based on a national sample which combines locations across various geographies each with a specific climate and regulatory setting. I examine changes in population and residential prices and interpret their joint dynamic to explain how weather surprises can reshape communities and their neighbors. In this part, I confirm that changes in quantities occur where prices do not adjust and vice versa by focusing on regions within the US. This ensures that the main results are not driven by outcomes in a particular state or region.

The regional results for population and house prices are listed in Table 8. The baseline population results are highly representative of different areas of the country. The population evidence shows that low-growth areas experience limited changes in all but two regions: the Northeast and the West. Population drops in all high-growth communities. In the West region, high-growth places experience much higher decrease in population, which is consistent with the relatively higher price compensation in low-growth places. In Northeast, the contemporaneous effects are similar for high- and low-growth locations but the persistent decline is slightly bigger for the high-growth ones. This is also consistent with the higher decline in residential prices in the low-growth communities. The results confirm that surprises affect population at high pre-growth communities.

Regional real estate results for all tiers are reported in Table 8. Prices in high-growth locations either remain constant or in some cases increase after unanticipated floods. The Northeast is the only exception to this since prices decline in high-growth places. Yet, they still decline less in relative terms. Prices in low-growth communities provide a compensating decline in all areas but the Midwest and the South Central. The difference in insurance reimbursement in these two regions suggested that low-historical-loss locations are more likely to experience unanticipated floods. The results here suggest that communities in these areas may ignore information from weather surprises as important for flood risk revision.

Relative Damage by Historic Loss: The results in this paper control for relative damage at the average location and do not allow the effect to differ by the extent of historic losses. Here, I relax this assumption. The results are shown in column(1) of Table 9. Higher relative damage reduces the overall negative effect of unanticipated flood on population. The evidence confirms that the main results in the paper are not driven by negative supply shocks. Lower-damage locations are more likely to experience population declines that are driven by changes in risk expectations. The insurance evidence showed that anticipation is much lower for low-damage events. Locations which experience higher damage are more likely to anticipate the event. These communities are distinct from the rest of the low-historical-loss places and are not affected by a flood surprise as much.

Local Social Organizations and Churches: The literature on resilience after natural disasters identifies the importance of local social capital Aldrich (2012). The 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 interact this number with the set of impact indicators as described above. The results for population are listed in column (2) of Table 9. The evidence shows that higher social capital weakens the decline in population both on impact and in the post period. 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. (2008). I am able to match a third of the baseline sample with the WRLURI and this limited sample. I interact the index with the set of controls for the impact indicators. For the case of local income, I use the 2000 Census and interact level of income, centered at the median value of 40 thousand. Results are listed in Table 9.

Column (3) shows that land regulation does not explain the population declines. Regulation has a similar negative impact on communities that anticipate and do not anticipate floods. This suggests that communities with higher regulation are more likely to invest in improving the housing stock after a flood surprise. As a result there will be a stronger population decline as living in these locations becomes relatively more expensive given the increase in expected risk. Column (4) reports the evidence using local income as a control. Communities with higher income experience stronger population contraction. The interpretation of this result is similar to the effect of stronger regulation. Higher local income allows more local homeowners to improve the housing stock. This leads to higher cost of living and reduces population as a result. In each case the additional controls do not change the main results, confirming that these are driven by changes in risk expectations which are only partially related to the robustness controls in this section.

Low-wealth Incidence: The identified responses to risk revisions in the main results rest on the assumption that households are not prevented from leaving. This is critical in the case of homeowners who may experience a lock-in effect if the value of their current house cannot cover the down payment and transactions cost of the house they would like to move into, as in Stein (1995). The lack of population responses in communities where expected risk increases can be due to the inability households to finance their way out. This can explain why some regions within the country seem to ignore flood surprises.

I examine the extent to which low wealth can explain the lack of population changes in low growth areas 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. I test whether flood incidence among low-wealth households is higher in low growth or low-historic-loss communities by examining total FEMA payments per damage recorded and how they differ in low-growth communities. I also do this for SBA loans.

Results, in columns (1) and (2) of Table 10, show that low-growth communities receive more FEMA relief, holding total and FEMA damage constant. Separating effects by regions we see that low-growth communities in the South Central area on average receive 15% more relief for the same level of damage and FEMA damages, compered to the rest. This explains the limited quantity and price effect in this region. Columns (3) and (4) of Table 10 show that low-historic-loss/low-growth communities in the Northeast region are more likely to finance losses through government loans. Since loans are used to improve housing, this is an indication that these places invest in risk-mitigation even in the low-growth category.

8 Conclusion

This study provides a description of the US flooding experience in the decade after 2003 with a carefully compiled data on insured and uninsured damage for each incorporated area. Flooding is a frequent and widespread concern nationwide. I show that when evaluating the impact of disasters, expectation revisions can be critical. Low historical flood experience and low-risk flood zones can identify instances where the share of uninsured losses is high and expected flood risk is low. Experience with or proximity to flooding due to these weather shocks can lead to risk revisions and can highlight the importance of risk in the location and risk-mitigation decision. I find that flooding leads to a sizable population decline primarily in areas with lower risk expectations. This is explained by growing communities where the higher value of real estate leads to investments in flood mitigations, keeping prices from falling and increasing the cost of new construction. These places grow slower and become more expensive to live in, suggesting that the flood-insurance-cost incentives, combined with increased risk expectations and high real estate value, make the community better prepared to absorb future losses. Less attractive places do not see population changes and higher risk leads to insurance compensating price declines. The lower house values, the decrease in the number of higher-income individuals, and the limited house investments suggests that weather shocks make these places less able to absorb future losses. This implies that global warming will generate divergence in loss exposure and reliance on government relief across communities based on they existing growth conditions.

Tables and Figures

Table 1: Relative and Absolute Damage for Communities with Different Flood Frequencies

		Relative Damage Distribution					Total Damage ($1 mil) Distribution				
	Obs	p25	p50	p75	p90	p95	p25	p50	p75	p90	p95
Communities with No Flooding	1,771	-	-	-	-	-	-	-	-	-	-
Communities with One Flood	1,519	0.02%	0.05%	0.14%	0.46%	1.03%	0.64	1.67	5.02	16.14	42.39
Communities with Two Floods	542	0.02%	0.06%	0.19%	0.69%	1.55%	0.64	1.80	5.70	20.75	47.18
Communities with Three Floods	238	0.02%	0.07%	0.25%	0.86%	1.72%	0.79	2.45	9.14	33.90	76.74
Communities with More than Three Floods	77	0.02%	0.09%	0.34%	1.27%	8.66%	0.83	3.42	13.50	69.68	213.80

The table lists the total number of communities and select percentiles for the distribution of relative/absolute damage for communities which experience one/two/three/more than three floods during the sample years of 2003-2013. A flood is an event with more than 0.01% total loss as a fraction of the community's real estate value. Two consecutive floods are are placed within the "one-flood" category.

Table 2: Summary Statistics by Historic Flood Loss and Historic Population Growth

	Communities with X Floods								HistLoss$^-$	HistLoss$^-$	HistLoss$^+$	HistLoss$^+$
	X=0	X=1	X=2	X>2	HistLoss$^-$	HistLoss$^+$	HistGr$^-$	HistGr$^+$	HistGr$^-$	HistGr$^+$	HistGr$^-$	HistGr$^+$
Count	1,771	1,519	542	315	934	585	400	1,119	229	705	171	414
Relative Damage	0	0.0027	0.0053	0.033	0.0022	0.0035	0.0027	0.0027	0.0016	0.0023	0.004	0.0033
	(0)	(0.0082)	(0.0174)	(0.168)	(0.0055)	(0.0112)	(0.0072)	(0.0085)	(0.0047)	(0.0058)	(0.0093)	(0.012)
Total $ Damage (1M)	0	12.94	13.53	163.8	7.918	20.90	9.108	14.37	3.573	9.313	15.80	23.28
	(0)	(50.20)	(42.45)	(1220.2)	(27.12)	(72.52)	(37.69)	(54.11)	(13.09)	(30.16)	(53.55)	(79.87)
Structures Lost (1978/2000)	0.0032	0.0079	0.019	0.039	0.0021	0.017	0.0097	0.0073	0.0023	0.0021	0.018	0.016
	(0.010)	(0.017)	(0.040)	(0.063)	(0.002)	(0.025)	(0.021)	(0.015)	(0.002)	(0.002)	(0.028)	(0.023)
Insurance Policies Per Cap	2.077	29.26	27.65	48.18	14.32	52.96	16.08	34.19	3.216	17.88	31.65	62.92
	(16.28)	(71.20)	(70.48)	(84.45)	(39.69)	(98.56)	(57.09)	(75.26)	(3.992)	(45.00)	(82.35)	(104.0)
Total % RE Coverage	0.00345	0.0406	0.0573	0.0782	0.0194	0.0741	0.0240	0.0468	0.00680	0.0235	0.0447	0.0879
	(0.0229)	(0.0944)	(0.126)	(0.123)	(0.0458)	(0.134)	(0.0851)	(0.0970)	(0.0164)	(0.0512)	(0.122)	(0.137)
Fraction in 100 year zone	0.0085	0.0591	0.0617	0.0986	0.0461	0.0798	0.0335	0.0687	0.0165	0.0555	0.0539	0.0919
	(0.042)	(0.144)	(0.112)	(0.145)	(0.132)	(0.158)	(0.110)	(0.153)	(0.0688)	(0.146)	(0.143)	(0.164)
Fraction in 500 year zone	0.0173	0.0432	0.0321	0.0364	0.0269	0.0691	0.00979	0.0557	0.00630	0.0335	0.0140	0.0949
	(0.0982)	(0.136)	(0.0897)	(0.0837)	(0.0992)	(0.177)	(0.0299)	(0.157)	(0.0272)	(0.112)	(0.0326)	(0.209)
Share of Insured Damages	0	0.223	0.261	0.384	0.188	0.278	0.194	0.233	0.144	0.202	0.256	0.288
	(0)	(0.292)	(0.318)	(0.349)	(0.281)	(0.301)	(0.281)	(0.296)	(0.239)	(0.292)	(0.316)	(0.295)
Share of Uninsured FEMA	0	0.228	0.217	0.166	0.241	0.207	0.270	0.212	0.286	0.227	0.251	0.186
	(0)	(0.188)	(0.193)	(0.162)	(0.187)	(0.188)	(0.215)	(0.174)	(0.211)	(0.176)	(0.219)	(0.169)
Share of Uninsured Business	0	0.122	0.107	0.0861	0.122	0.121	0.111	0.126	0.112	0.125	0.109	0.127
	(0)	(0.166)	(0.158)	(0.137)	(0.167)	(0.164)	(0.158)	(0.168)	(0.151)	(0.172)	(0.168)	(0.162)
Share of Uninsured Home	0	0.285	0.316	0.239	0.306	0.252	0.283	0.285	0.301	0.307	0.262	0.247
	(0)	(0.199)	(0.221)	(0.200)	(0.206)	(0.184)	(0.201)	(0.198)	(0.211)	(0.204)	(0.188)	(0.182)
Population (100k)	0.636	0.651	0.799	0.671	0.595	0.740	0.524	0.699	0.551	0.609	0.490	0.857
	(1.382)	(0.929)	(1.789)	(0.964)	(0.901)	(0.966)	(0.772)	(0.977)	(0.925)	(0.894)	(0.536)	(1.093)
Median Income (100k)	0.468	0.439	0.427	0.425	0.434	0.447	0.367	0.466	0.360	0.458	0.376	0.480
	(0.253)	(0.194)	(0.161)	(0.220)	(0.184)	(0.209)	(0.157)	(0.200)	(0.138)	(0.191)	(0.177)	(0.214)
Population Growth	0.0074	0.0088	0.0086	0.00009	0.010	0.005	-0.003	0.013	-0.003	0.015	-0.004	0.010
	(0.014)	(0.016)	(0.017)	(0.091)	(0.017)	(0.014)	(0.007)	(0.016)	(0.007)	(0.017)	(0.008)	(0.014)
Top Tier House Value	0.296	0.260	0.224	0.249	0.240	0.292	0.159	0.298	0.136	0.273	0.186	0.342
	(0.319)	(0.231)	(0.188)	(0.215)	(0.202)	(0.267)	(0.262)	(0.206)	(0.213)	(0.187)	(0.311)	(0.229)
Middle Tier House Value	0.200	0.175	0.144	0.163	0.162	0.196	0.107	0.201	0.0910	0.185	0.126	0.229
	(0.214)	(0.153)	(0.127)	(0.133)	(0.136)	(0.174)	(0.167)	(0.139)	(0.128)	(0.131)	(0.205)	(0.148)
Bottom Tier House Value	0.136	0.117	0.0962	0.107	0.108	0.132	0.0741	0.133	0.0632	0.122	0.0873	0.152
	(0.154)	(0.115)	(0.0974)	(0.101)	(0.100)	(0.134)	(0.124)	(0.107)	(0.0874)	(0.0997)	(0.157)	(0.117)

Table lists averages and standard deviation for groups of communities defined in four distinct ways. The first panel shows statistics by communities with no/one/two/two plus floods in the sample. The second panel divides the communities which experience one flood (or two consecutive) relative to the state median of historic flood loss. HistLoss$^-$/HistLoss$^+$ includes communities below/above the median. Historic flood loss is defined as the total structures lost to flooding in the community relative to the number of current structures. The third panel divides the communities which experience one flood depending on their historical population growth. HistGr$^-$/HistGr$^+$ includes communities with non-positive/positive population growth in the three years prior to their flooding. The final panel interacts the historic loss and population growth categories.

Table 3: Historic Loss, Flood Zones, and Flood Insurance

VARIABLES	(1) Log Flood Insurance Payouts Per Person	(2)	(3) Share Flood Insured Damages	(4)	(5) Log Flood Insurance Policies Per Person	(6)
$\mathbb{1}(1Flood)$	-0.183	0.0263	0.0224	0.0225	-0.812**	-0.883**
	(0.176)	(0.205)	(0.0142)	(0.0143)	(0.293)	(0.321)
$\mathbb{1}(1Flood) \times Damage$	0.798***	0.738***	0.436	0.576	0.0415	0.0621
	(0.0743)	(0.0941)	(1.023)	(0.716)	(0.0449)	(0.0644)
$\mathbb{1}(1Flood) \times HistLoss^{+}$	0.793***	0.116	0.0639***	0.0645***	1.561***	1.735***
	(0.119)	(0.232)	(0.0166)	(0.0174)	(0.108)	(0.314)
$\mathbb{1}(1Flood) \times HistLoss^{+} \times Damage$		0.169**		-0.753		-0.0414
		(0.0664)		(1.149)		(0.0641)
$\mathbb{1}(1Flood) \times$ *Share 500-year Zone*	-0.103	2.721***	0.0395	-0.0108	2.461***	2.839***
	(0.500)	(0.617)	(0.0315)	(0.0256)	(0.389)	(0.646)
$\mathbb{1}(1Flood) \times$ *Share 500-year Zone* $\times$ *Damage*		-0.614***		14.18***		-0.0718
		(0.170)		(4.345)		(0.159)
Observations	3,439	3,439	3,562	3,562	1,473	1,473
R-squared	0.603	0.605	0.605	0.605	0.570	0.570
State-Year FE	X	X	X	X	X	X
Additional Controls	X	X	X	X	X	X
Sample	All Floods	All Floods	All Floods	All Floods	2005/2006/2010	2005/2006/2010

Notes: *** p<0.01, ** p<0.05, * p<0.1. The table includes results from estimating a cross-sectional model of all flood events in the sample. Columns (5) and (6) use a subset of the sample when insurance policy information is available (years 2005, 2006m and 2010). Floods are defined as instances with more than 0.01% of damage as a fraction of local real estate. $\mathbb{1}(1Flood)$ is an indicator for the occurrence of one (or two consecutive) flood during the sample. *Damage* is total damage per capita in (1)-(2), (5)-(6) and damage as a fraction of local real estate value in (3)-(4). *Share 500-year Zone* is the share of housing in the 500-year flood zone. $HistLoss^{+}$ is an indicator for above-median historical loss. Additional controls estimated but not reported are: share of housing in the 100-year zones, the share of damage affecting households which receive FEMA non-refundable relief, the share of damages affecting households which receive SBA loans, the share of damages affecting businesses which receive SBA business loans. I also include but do not report a set of indicators and damage controls for communities which are affected by more than one flood. Sample covers the period between 2000 and 2016. SE clustered by state.

Table 4: Floods, Historical Loss, and Population Changes

	Log Population$_{it}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Historical Loss:		State Median Lost Structures			0.1% Lost Structures	25% Insurance Coverage	Floods: 0.0075% Relative Damage
$\mathbb{1}(1Flood)\mathbb{1}(t = Flood)$	-0.000832	-0.00566**					
	(0.00112)	(0.00260)					
$\mathbb{1}(1Flood)\mathbb{1}(t > Flood)$	-0.00396***	-0.00564**					
	(0.00144)	(0.00262)					
$\mathbb{1}(1Flood)\mathbb{1}(t > Flood)t$	-4.14e-05	-0.00212***					
	(0.000484)	(0.000690)					
Low Historical Loss							
$\mathbb{1}(1Flood)\mathbb{1}(t = Flood)$			-0.00307**	-0.00928***	-0.0113***	-0.00807**	-0.00803**
			(0.00120)	(0.00347)	(0.00389)	(0.00339)	(0.00321)
$\mathbb{1}(1Flood)\mathbb{1}(t > Flood)$			-0.00463***	-0.00794**	-0.00895**	-0.00838**	-0.00648**
			(0.00174)	(0.00341)	(0.00415)	(0.00352)	(0.00323)
$\mathbb{1}(1Flood)\mathbb{1}(t > Flood)t$			-0.00146**	-0.00365***	-0.00454***	-0.00259***	-0.00326***
			(0.000583)	(0.000779)	(0.000924)	(0.000845)	(0.000782)
High Historical Loss							
$\mathbb{1}(1Flood)\mathbb{1}(t = Flood)$			0.00293	-0.000500	-0.00383*	-0.00445*	-0.000528
			(0.00193)	(0.00175)	(0.00230)	(0.00236)	(0.00172)
$\mathbb{1}(1Flood)\mathbb{1}(t > Flood)$			-0.00261	-0.00218	-0.00460*	-0.00422*	-0.00222
			(0.00218)	(0.00214)	(0.00241)	(0.00250)	(0.00213)
$\mathbb{1}(1Flood)\mathbb{1}(t > Flood)t$			0.00215***	-2.95e-05	-0.00132*	-0.00190**	9.32e-05
			(0.000615)	(0.000738)	(0.000716)	(0.000754)	(0.000754)
Controls for Single-Flood Communities							
Relative Damage							
$\mathbb{1}(1Flood)\mathbb{1}(t = Flood)$		0.0592		-0.0349	0.0214	0.0663	-0.0769
		(0.0682)		(0.0732)	(0.0686)	(0.0689)	(0.0854)
$\mathbb{1}(1Flood)\mathbb{1}(t > Flood)$		0.00976		-0.0660	-0.0149	0.0179	-0.116
		(0.117)		(0.119)	(0.119)	(0.118)	(0.126)
$\mathbb{1}(1Flood)\mathbb{1}(t > Flood)t$		0.0862***		0.0515	0.0692**	0.0886***	0.0375
		(0.0328)		(0.0324)	(0.0325)	(0.0330)	(0.0323)
500-year Flood Zone							
$\mathbb{1}(1Flood)\mathbb{1}(t = Flood)$		-0.0323*		-0.0391**	-0.0348**	-0.0308*	-0.0365**
		(0.0171)		(0.0164)	(0.0163)	(0.0166)	(0.0180)
$\mathbb{1}(1Flood)\mathbb{1}(t > Flood)$		-0.0780***		-0.0832***	-0.0795***	-0.0761***	-0.0801***
		(0.0244)		(0.0236)	(0.0236)	(0.0238)	(0.0253)
$\mathbb{1}(1Flood)\mathbb{1}(t > Flood)t$		0.0105		0.00776	0.00941	0.0109*	0.00749
		(0.00661)		(0.00627)	(0.00630)	(0.00653)	(0.00668)
Fema Damage							
$\mathbb{1}(1Flood)\mathbb{1}(t = Flood)$		0.0216		0.0244	0.0234	0.0216	0.0173
		(0.0146)		(0.0150)	(0.0148)	(0.0145)	(0.0143)
$\mathbb{1}(1Flood)\mathbb{1}(t > Flood)$		0.0161		0.0178	0.0169	0.0161	0.00956
		(0.0136)		(0.0138)	(0.0137)	(0.0135)	(0.0134)
$\mathbb{1}(1Flood)\mathbb{1}(t > Flood)t$		0.00398		0.00511**	0.00485*	0.00402	0.00283
		(0.00263)		(0.00259)	(0.00257)	(0.00262)	(0.00276)
Observations	70,403	70,403	70,403	70,403	70,403	70,403	70,403
Within R-squared	0.00500	0.0248	0.00786	0.0280	0.0269	0.0251	0.0268
Town FE	X	X	X	X	X	X	X
State x Year FE	X	X	X	X	X	X	X
Town Linear Trend	X	X	X	X	X	X	X
Additional Controls		X		X	X	X	X

Notes: *** p<0.01, ** p<0.05, * p<0.1.$\mathbb{1}(t = Flood)$ is an indicator for flood event. $\mathbb{1}(t > Flood)$ is an indicator for the period following the first year of impact. $t \times \mathbb{1}(t > Flood)$ is a linear trend starting the in the period following the impact. *Low/High Historical Loss* is an indicator based on the state median lost structures between 1978 and 2003. *Relative Damage* is total damage as a share of real estate value. *Sh500-yearFloodZone* is the share of housing in the 500-year flood zone. *Fema Damage* is fraction of damages covered by government relief. The additional controls for *Share Construction/Share Renters* are included where indicated in the table. All results include but do not report coefficients for multiple-flood communities. Estimation (5) and (6) use a different definitions for low historical loss and high surprise – less than 0.1% destroyed structures; less than 25% of population in the 100-year zone has insurance. Sample: 2000/2016. SE clustered by community. Estimation (7) uses a different definition for floods – events with relative damage above 0.00075% (the median relative damage for cases with over $1,000 of absolute damage).

Table 5: Population: Flood Surprises, Historical Growth

		Log Population$_{it}$			
		(1)	(2)	(3)	(4)
	Historical Loss:	State Median Lost Structures		0.1% Lost Structures	25% Insurance Coverage
Low Historical Loss — *High Pre Growth*	$\mathbb{1}(t = Flood)$	-0.00550***	-0.0107***	-0.0125***	-0.00866***
		(0.00142)	(0.00328)	(0.00389)	(0.00321)
	$\mathbb{1}(t > Flood)$	-0.00538***	-0.00823**	-0.00794*	-0.00692**
		(0.00207)	(0.00333)	(0.00436)	(0.00349)
	$t\mathbb{1}(t > Flood)$	-0.00409***	-0.00545***	-0.00644***	-0.00430***
		(0.000656)	(0.000769)	(0.000978)	(0.000858)
Low Historical Loss — *Low Pre Growth*	$\mathbb{1}(t = Flood)$	0.00657***	-0.00128	-0.00222	-0.000201
		(0.00115)	(0.00399)	(0.00388)	(0.00480)
	$\mathbb{1}(t > Flood)$	0.000965	-0.00369	-0.00605	-0.00734
		(0.00189)	(0.00392)	(0.00428)	(0.00459)
	$t\mathbb{1}(t > Flood)$	0.00681***	0.00449***	0.00418***	0.00659***
		(0.000601)	(0.000889)	(0.00103)	(0.00103)
		Controls for Single-Flood Communities			
Relative Damage	$\mathbb{1}(t = Flood)$		-0.0705	-0.0153	0.0212
			(0.0711)	(0.0616)	(0.0604)
	$\mathbb{1}(t > Flood)$		-0.125	-0.0768	-0.0472
			(0.107)	(0.104)	(0.104)
	$t\mathbb{1}(t > Flood)$		0.0472*	0.0617**	0.0743***
			(0.0258)	(0.0256)	(0.0260)
500-year Flood Zone	$\mathbb{1}(t = Flood)$		-0.0353**	-0.0311*	-0.0281*
			(0.0163)	(0.0164)	(0.0168)
	$\mathbb{1}(t > Flood)$		-0.0826***	-0.0784***	-0.0761***
			(0.0237)	(0.0237)	(0.0241)
	$t\mathbb{1}(t > Flood)$		0.0118*	0.0131**	0.0142**
			(0.00634)	(0.00635)	(0.00661)
Fema Dam	$\mathbb{1}(t = Flood)$		0.0230	0.0220	0.0203
			(0.0146)	(0.0142)	(0.0141)
	$\mathbb{1}(t > Flood)$		0.0178	0.0166	0.0162
			(0.0134)	(0.0131)	(0.0130)
	$t\mathbb{1}(t > Flood)$		0.00297	0.00287	0.00202
			(0.00246)	(0.00241)	(0.00247)
	Observations	70,403	70,403	70,403	70,403
	Within R-squared	0.0269	0.0439	0.0432	0.0419
	Town FE	X	X	X	X
	State x Year FE	X	X	X	X
	Town Linear Trend	X	X	X	X
	Additional Controls		X	X	X

Notes: *** p<0.01, ** p<0.05, * p<0.1.$\mathbb{1}(t = Flood)$ is an indicator for flood event. $\mathbb{1}(t > Flood)$ is an indicator for the period following the first year of impact. $t \times \mathbb{1}(t > Flood)$ is a linear trend starting the in the period following the impact. *Low/High Historical Loss* is an indicator based on the state median lost structures between 1978 and 2003. *Low/High Pre Growth* refers to non-positive population growth before the flood/positive growth before the flood. *Relative Damage* is total damage as a share of real estate value. *Sh500-yearFloodZone* is the share of housing in the 500-year flood zone. *Fema Damage* is fraction of damages covered by government relief. The additional controls for *Share Construction/Share Renters* are included where indicated in the table. All results include but do not report coefficients for multiple-flood communities. Estimation (3) and (4) use a different definitions for low historical loss and high surprise – less than 0.1% destroyed structures; less than 25% of population in the 100-year zone has insurance. Sample: 2000/2016. SE clustered by community. The estimation results do not report the coefficients for multiple-flood communities.

Table 6: Real Estate Values: Flood Surprises, Historic Growth

		Top Tier Housing	Middle Tier Housing	Low Tier Housing	Top Tier Housing	Top Tier Housing	Remod Establish	No Mail Service
		(1)	(2)	(3)	(4)	(5)	(6)	(7)
Historical Loss:			State Median Lost Structures		0.1% Lost Structures	25% Insur Coverage	State Median	State Median
Low Historical Loss *High Pre Growth*	$\mathbb{1}(t = Flood)$	0.00176	0.00359	0.00856	-0.00425	-0.00249	0.0373*	-0.00109
		(0.00588)	(0.00627)	(0.00755)	(0.00795)	(0.00641)	(0.0220)	(0.00255)
	$\mathbb{1}(t > Flood)$	0.000276	0.00483	0.00116	0.00540	-0.00176	0.00679	-0.000448
		(0.00780)	(0.00781)	(0.00943)	(0.0104)	(0.00781)	(0.0270)	(0.00278)
	$t\mathbb{1}(t > Flood)$	-0.000168	-0.00139	-0.00132	0.00156	0.00316	0.0358***	0.000180
		(0.00203)	(0.00208)	(0.00238)	(0.00264)	(0.00205)	(0.0107)	(0.000858)
Low Historical Loss *Low Pre Growth*	$\mathbb{1}(t = Flood)$	-0.0268**	-0.0249**	-0.0235*	-0.0424***	-0.0524***	-0.0118	-0.00907**
		(0.0107)	(0.0119)	(0.0136)	(0.0152)	(0.0125)	(0.0322)	(0.00394)
	$\mathbb{1}(t > Flood)$	-0.0374***	-0.0415***	-0.0531***	-0.0445**	-0.0605***	-0.00806	-0.00689*
		(0.0132)	(0.0156)	(0.0178)	(0.0182)	(0.0156)	(0.0399)	(0.00397)
	$t\mathbb{1}(t > Flood)$	0.00510	0.00403	0.00713*	-9.57e-05	0.00261	-0.00221	0.000158
		(0.00313)	(0.00359)	(0.00418)	(0.00447)	(0.00431)	(0.0151)	(0.00120)
				Controls for Single-Flood Communities				
Relative Damage	$\mathbb{1}(t = Flood)$	0.163	-0.119	-0.382	0.176	0.210	2.914**	0.0947
		(0.294)	(0.321)	(0.347)	(0.290)	(0.280)	(1.139)	(0.112)
	$\mathbb{1}(t > Flood)$	-0.292	-0.651	-1.043**	-0.239	-0.251	4.349***	0.441***
		(0.369)	(0.419)	(0.432)	(0.361)	(0.359)	(1.399)	(0.123)
	$t\mathbb{1}(t > Flood)$	-0.0275	-0.0605	-0.111	-0.0269	-0.0346	-0.0804	-0.00533
		(0.0680)	(0.0678)	(0.0709)	(0.0668)	(0.0663)	(0.507)	(0.0418)
500-year Flood Zone	$\mathbb{1}(t = Flood)$	-0.0353	-0.00276	0.0102	-0.0356	-0.0317	0.0758	-3.33e-05
		(0.0288)	(0.0288)	(0.0419)	(0.0286)	(0.0287)	(0.134)	(0.0117)
	$\mathbb{1}(t > Flood)$	-0.162***	-0.167***	-0.209***	-0.159***	-0.159***	0.0636	-0.00353
		(0.0463)	(0.0476)	(0.0633)	(0.0453)	(0.0453)	(0.166)	(0.00782)
	$t\mathbb{1}(t > Flood)$	-0.0179**	-0.0220**	-0.0379***	-0.0178**	-0.0171**	0.0521	0.0181***
		(0.00734)	(0.00911)	(0.0106)	(0.00708)	(0.00698)	(0.0642)	(0.00664)
Fema Dam	$\mathbb{1}(t = Flood)$	-0.00970	-0.0134	-0.0135	-0.00908	-0.0110	-0.0353	-0.00174
		(0.0199)	(0.0197)	(0.0243)	(0.0202)	(0.0194)	(0.0709)	(0.00729)
	$\mathbb{1}(t > Flood)$	-0.00668	-0.0167	-0.0158	-0.0103	-0.00807	0.0302	-0.00590
		(0.0278)	(0.0253)	(0.0295)	(0.0284)	(0.0271)	(0.0880)	(0.00820)
	$t\mathbb{1}(t > Flood)$	-0.00340	0.00293	-0.000339	-0.00391	-0.00296	-0.0505	0.00112
		(0.00630)	(0.00587)	(0.00723)	(0.00652)	(0.00620)	(0.0326)	(0.00245)
Observations		61,530	60,920	54,554	61,530	61,530	51,031	38,481
Within R-squared		0.0168	0.0187	0.0179	0.0169	0.0180	0.00421	0.00267
Town FE		X	X	X	X	X	X	X
State x Year FE		X	X	X	X	X	X	X
Town Linear Trend		X	X	X	X	X	X	X
Additional Controls		X	X	X	X	X	X	X

Notes: *** p<0.01, ** p<0.05, * p<0.1. Top/Middle/BottomTier refers to the log of the respective house price Zillow index. Remodeling Establish refers to the log of establishments engaged in house remodeling (NAICS 236118). No Mail service refers to the fraction of houses which are designated as No Service in the USPS mailing dataset. $\mathbb{1}(t = Flood)$ is an indicator for flood event. $\mathbb{1}(t > Flood)$ is an indicator for the period following the first year of impact. $t\mathbb{1}(t > Flood)$ is a linear trend starting the in the period following the impact. *Low/High Historical Loss* is an indicator based on the state median lost structures between 1978 and 2003. *Low/High Pre Growth* refers to non-positive population growth before the flood/positive growth before the flood. *Relative Damage* is total damage as a share of real estate value. *Sh500-yearFloodZone* is the share of housing in the 500-year flood zone. *Fema Damage* is fraction of damages covered by government relief. The estimation results do not report the coefficients for *Share Construction*/*Share Renters* and multiple-flood communities. Estimation (3) and (4) use a different definitions for low historical loss and high surprise – less than 0.1% destroyed structures; less than 25% of population in the 100-year zone has insurance. Sample: 2000/2016. SE clustered by community. The estimation results do not report the coefficients for multiple-flood communities.

Table 7: Flood Spillovers

	VARIABLES	(1) Log Pop	(2) Top Tier	(3) Mid Tier	(4) Low Tier
No Flood County	No Direct Damage ×				
	$I(t = NextOneFlood)$	-0.000538	0.00308	0.00436	0.00787**
		(0.000722)	(0.00315)	(0.00325)	(0.00400)
	$I(t = NextTwoFloods)$	0.00338***	0.00711*	0.0111***	0.0126***
		(0.00113)	(0.00372)	(0.00398)	(0.00460)
	$I(t = NextThreeFloods)$	-0.00279**	-0.0117***	-0.0189***	-0.0168***
		(0.00123)	(0.00407)	(0.00434)	(0.00498)
Flood County	No Direct Damage ×				
	$I(t = NeighborFlood)$	-0.0140***	-0.0138**	-0.0197***	-0.0140**
		(0.00308)	(0.00607)	(0.00609)	(0.00698)
	$I(t > NeighborFlood)$	-0.0157***	-0.0151**	-0.0224***	-0.0252***
		(0.00369)	(0.00726)	(0.00730)	(0.00866)
	$tI(t > NeighborFlood)$	-0.00331***	0.00121	-7.34e-05	0.00122
		(0.00104)	(0.00208)	(0.00213)	(0.00249)
Flood County	Direct Damage ×				
	$I(t = Flood)$	-0.00603**	0.000337	0.00174	0.00531
		(0.00260)	(0.00532)	(0.00553)	(0.00669)
	$I(t > Flood)$	-0.00627**	-0.00232	-0.000207	-0.00795
		(0.00263)	(0.00678)	(0.00687)	(0.00855)
	$tI(t > Flood)$	-0.00203***	0.000553	-0.00154	-0.000563
		(0.000709)	(0.00187)	(0.00198)	(0.00228)
		Controls for Flood County / No Direct Damage			
	Relative Damage ×				
	$I(t = NeighborFlood)$	0.0572	0.152	-0.100	-0.405
		(0.0688)	(0.302)	(0.320)	(0.344)
	$I(t > NeighborFlood)$	0.00997	-0.257	-0.617	-1.059**
		(0.118)	(0.359)	(0.398)	(0.411)
	$tI(t > NeighborFlood)$	0.0845**	-0.0336	-0.0646	-0.106
		(0.0330)	(0.0658)	(0.0657)	(0.0686)
	500-year Flood Zone ×				
	$I(t = NeighborFlood)$	-0.0314*	-0.0262	0.00240	0.0119
		(0.0167)	(0.0290)	(0.0289)	(0.0420)
	$I(t > NeighborFlood)$	-0.0777***	-0.150***	-0.160***	-0.200***
		(0.0239)	(0.0457)	(0.0476)	(0.0639)
	$tI(t > NeighborFlood)$	0.0111*	-0.0198***	-0.0236***	-0.0392***
		(0.00653)	(0.00708)	(0.00899)	(0.0104)
	Fema Dam ×				
	$I(t = NeighborFlood)$	0.0210	-0.0179	-0.0218	-0.0207
		(0.0146)	(0.0198)	(0.0195)	(0.0242)
	$I(t > NeighborFlood)$	0.0154	-0.0176	-0.0274	-0.0263
		(0.0136)	(0.0276)	(0.0254)	(0.0296)
	$tI(t > NeighborFlood)$	0.00377	-0.00161	0.00462	0.00128
		(0.00263)	(0.00633)	(0.00600)	(0.00724)
	Observations	70,403	61,530	60,920	54,554
	Within R-squared	0.0391	0.0228	0.0230	0.0211
	Town FE	X	X	X	X
	State x Year FE	X	X	X	X
	Town Linear Trend	X	X	X	X
	Additional Controls	X	X	X	X

Notes: *** p<0.01, ** p<0.05, * p<0.1. *No Flood County* refers to places in unaffected counties. *Flood County* refers to places in a county with a single-flood community. $I(t = NextOneFlood)/I(t = NextTwoFloods)/I(t = NextThreeFloods)$ is the effect of being next to a county with one/two/three-plus floods. $I(t = NeighborFlood)$ indicates the year of the single flood of the neighbor. $I(t > NeighborFlood)$ indicates the period after the single flood of the neighbor. $tI(t > NeighborFlood)$ allows for a trend-break after the single flood of the neighbor. Sample: 2000/2016. SE clustered by community. For more information of the controls consult Table 5

Table 8: Regional Responses to Flood Surprises: Population and RE

		(1) Population Low Historical Loss		(2) Top Tier RE Low Historical Loss		(3) Mid Tier RE Low Historical Loss		(4) Low Tier RE Low Historical Loss	
		Low Growth	High Growth	Low Growth	High Growth	Low Growth	High Growth	Low Growth	High Growth
Northeast	$\mathbb{1}(t = Flood)$	-0.0123***	-0.0151***	-0.0255*	-0.0297***	-0.0118	-0.0221**	-0.0224	-0.0154
		(0.00464)	(0.00420)	(0.0145)	(0.0107)	(0.0155)	(0.0110)	(0.0179)	(0.0137)
	$\mathbb{1}(t > Flood)$	-0.0110**	-0.0133***	-0.0470**	-0.0418**	-0.0513**	-0.0388**	-0.0515**	-0.0259
		(0.00545)	(0.00502)	(0.0197)	(0.0167)	(0.0231)	(0.0170)	(0.0250)	(0.0188)
	$t\mathbb{1}(t > Flood)$	-0.00385**	-0.00599***	-0.00280	-0.00558	-0.000213	-0.00720	-0.00149	-0.0110*
		(0.00156)	(0.00158)	(0.00544)	(0.00543)	(0.00526)	(0.00514)	(0.00581)	(0.00560)
Mid-Atlantic	$\mathbb{1}(t = Flood)$	-0.00363	-0.0107**	-0.0382*	-0.0299**	-0.0440**	-0.0380***	-0.0504***	-0.0372**
		(0.00463)	(0.00429)	(0.0202)	(0.0131)	(0.0199)	(0.0144)	(0.0188)	(0.0156)
	$\mathbb{1}(t > Flood)$	-0.00508	-0.00510	-0.100***	-0.0373*	-0.119***	-0.0372*	-0.138***	-0.0452*
		(0.00623)	(0.00508)	(0.0230)	(0.0197)	(0.0248)	(0.0204)	(0.0227)	(0.0232)
	$t\mathbb{1}(t > Flood)$	0.00442***	-0.00631***	0.0206***	-0.00520	0.0210***	-0.00726	0.0220***	-0.0105
		(0.00160)	(0.00160)	(0.00653)	(0.00654)	(0.00775)	(0.00654)	(0.00736)	(0.00738)
Midwest	$\mathbb{1}(t = Flood)$	-0.00158	-0.0140***	-0.0338*	-0.00114	-0.0220	0.00172	-0.0152	0.0128
		(0.00470)	(0.00423)	(0.0184)	(0.00981)	(0.0198)	(0.0122)	(0.0217)	(0.0134)
	$\mathbb{1}(t > Flood)$	-0.00251	-0.0120***	-0.0318	-0.000316	-0.0234	0.00930	0.00119	0.00436
		(0.00503)	(0.00463)	(0.0205)	(0.0135)	(0.0244)	(0.0136)	(0.0312)	(0.0153)
	$t\mathbb{1}(t > Flood)$	0.00381***	-0.00534***	-0.00228	-0.00395	-0.00680	-0.00419	-0.0112*	-0.00557
		(0.00122)	(0.00125)	(0.00478)	(0.00280)	(0.00551)	(0.00300)	(0.00673)	(0.00348)
South Atlantic	$\mathbb{1}(t = Flood)$	0.00202	-0.00790**	-0.0728***	0.0444***	-0.0284	0.0414***	-0.0610	0.0389**
		(0.00570)	(0.00372)	(0.0241)	(0.0103)	(0.0211)	(0.0114)	(0.0418)	(0.0155)
	$\mathbb{1}(t > Flood)$	-0.000796	-0.00281	-0.0498	0.0262*	-0.0363	0.0254*	-0.0531	0.0280
		(0.00712)	(0.00521)	(0.0368)	(0.0143)	(0.0492)	(0.0150)	(0.0486)	(0.0196)
	$t\mathbb{1}(t > Flood)$	0.00699***	-0.00500***	-0.0163*	0.0105**	-0.00573	0.00782*	-0.00655	0.00702
		(0.00213)	(0.00180)	(0.00840)	(0.00429)	(0.0103)	(0.00434)	(0.0119)	(0.00463)
South Central	$\mathbb{1}(t = Flood)$	0.000695	-0.0102**	0.0125	0.0175*	-0.0147	0.0208**	0.000400	0.0157
		(0.00397)	(0.00416)	(0.0186)	(0.00959)	(0.0268)	(0.00975)	(0.0426)	(0.0139)
	$\mathbb{1}(t > Flood)$	-0.000692	-0.00597	0.0204	0.0205*	0.00301	0.0183	-0.0291	-0.00355
		(0.00542)	(0.00560)	(0.0263)	(0.0114)	(0.0338)	(0.0121)	(0.0435)	(0.0162)
	$t\mathbb{1}(t > Flood)$	0.00411**	-0.00599***	0.00877	0.00109	0.00648	0.00128	0.0180***	0.00517
		(0.00167)	(0.00144)	(0.00706)	(0.00330)	(0.00643)	(0.00362)	(0.00642)	(0.00445)
West	$\mathbb{1}(t = Flood)$	-0.00293	-0.0151***	-0.150***	0.0378**	-0.277***	0.0424**	-0.378***	0.0521**
		(0.00369)	(0.00496)	(0.0106)	(0.0168)	(0.0113)	(0.0169)	(0.0132)	(0.0217)
	$\mathbb{1}(t > Flood)$	0.00116	-0.0174***	-0.170***	0.0595***	-0.285***	0.0638***	-0.354***	0.0724***
		(0.00459)	(0.00657)	(0.0123)	(0.0213)	(0.0138)	(0.0226)	(0.0163)	(0.0259)
	$t\mathbb{1}(t > Flood)$	0.00560***	-0.00961***	-0.00499	-0.0125***	0.00897**	-0.0137**	0.00663	-0.0111**
		(0.00155)	(0.00199)	(0.00306)	(0.00449)	(0.00352)	(0.00535)	(0.00407)	(0.00506)
Observations		69,695		61,454		60,825		54,459	
Within R-squared		0.0555		0.0336		0.0348		0.0359	
Town FE		X		X		X		X	
State x Year FE		X		X		X		X	
Town Linear Trend		X		X		X		X	
Additional Controls		X		X		X		X	

Notes: *** p<0.01, ** p<0.05, * p<0.1. $I(t = Flood)$ is an indicator for flood event. $I(t > Flood)$ is an indicator for the period following the first year of impact. $tI(t > Flood)$ is a linear trend starting the in the period following the impact. Low Historical Loss is an indicator based on the state median lost structures between 1978 and 2003. Low/High Pre Growth refers to non-positive population growth before the flood/positive growth before the flood. Sample: 2000/2016. SE clustered by community. The estimation results do not report the coefficients for multiple-flood communities. I have split region 1 into Northeast and Mid-Atlantic and region 3 into South Atlantic and South Central. For more information of the controls consult Table 3

Table 9: Robustness: Damage, Social Organizations, Land Regulation, and Income

		(1)	(2)	(3)	(4)
		Log Population			
		X_i :Relative Damage	X_i :Social Organizations	X_i :Land Regulation	X_i :Relative Income
Low Historical Loss	$\mathbb{1}(t = Flood)$	-0.00677***	-0.00704***	-0.00987***	-0.00644***
		(0.00234)	(0.00235)	(0.00320)	(0.00231)
	$\mathbb{1}(t > Flood)$	-0.00613***	-0.00538***	-0.00791**	-0.00421**
		(0.00187)	(0.00194)	(0.00312)	(0.00184)
	$t\mathbb{1}(t > Flood)$	-0.00262***	-0.00309***	-0.00471***	-0.00256***
		(0.000602)	(0.000614)	(0.00112)	(0.000578)
	$\mathbb{1}(t = Flood) \times X_i$	0.510*	0.00726***	-0.00156	-5.22e-05
		(0.302)	(0.00223)	(0.00203)	(5.67e-05)
	$\mathbb{1}(t > Flood) \times X_i$	0.560**	0.00564*	-0.000588	-0.000205**
		(0.219)	(0.00332)	(0.00283)	(8.81e-05)
	$t\mathbb{1}(t > Flood) \times X_i$	0.146	0.00481***	-0.00181**	2.00e-05
		(0.0910)	(0.000964)	(0.000861)	(3.11e-05)
High Historical Loss	$\mathbb{1}(t = Flood)$	0.000250	0.000679	-0.00129	0.000278
		(0.00152)	(0.00163)	(0.00285)	(0.00158)
	$\mathbb{1}(t > Flood)$	-0.00196	-0.00272	-0.00549*	-0.00143
		(0.00208)	(0.00231)	(0.00321)	(0.00230)
	$t\mathbb{1}(t > Flood)$	0.00129**	0.00156**	0.000614	0.00117*
		(0.000623)	(0.000652)	(0.00119)	(0.000643)
	$\mathbb{1}(t = Flood) \times X_i$	-0.182***	-0.000798	-0.00308	-5.69e-06
		(0.0598)	(0.00404)	(0.00209)	(6.29e-05)
	$\mathbb{1}(t > Flood) \times X_i$	-0.136	0.00174	-0.00803**	-0.000121
		(0.0889)	(0.00426)	(0.00315)	(0.000110)
	$t\mathbb{1}(t > Flood) \times X_i$	0.0425	-0.000159	0.000346	3.18e-05
		(0.0338)	(0.00108)	(0.00121)	(3.21e-05)
Observations		70,403	70,403	23,747	69,695
Within R-squared		0.0150	0.0155	0.0210	0.0159
Town FE		X	X	X	X
State x Year FE		X	X	X	X
Town Linear Trend		X	X	X	X
Additional Controls		X	X	X	X

Notes: *** p<0.01, ** p<0.05, * p<0.1. Relative Damage refers to total damage at community i scaled by the value of real estate. Social organizations refers to the total number of civic and social organizations (NAICS 813410) and religious organizations (NAICS 813110) per capita. Land regulation refers to the Wharton Residential Land Use Regulation Index. Relative income refers to the median personal income centered at \$40K. $I(t = Flood)$ is an indicator for flood event. $I(t > Flood)$ is an indicator for the period following the first year of impact. $t \times I(t > Flood)$ is a linear trend starting the in the period following the impact. Low/High Historical Loss is an indicator based on the state median lost structures between 1978 and 2003. Sample: 2000/2016. SE clustered by community.

Table 10: Low-wealth Incidence of Floods

VARIABLES	(1) Log FEMA Relief Per Capita	(2)	(3) Log SBA Loans Per Capita	(4)
$I(OneFlood_i)$	-0.182*	-0.181*	-0.753***	-0.726***
	(0.0959)	(0.0932)	(0.137)	(0.141)
$I(OneFlood_i) \times LogDamage_i$	-0.0913***	-0.0874***	0.00489	0.00307
	(0.0284)	(0.0280)	(0.0314)	(0.0319)
$I(OneFlood_i) \times LogFEMADamage_i$	1.019***	1.020***		
	(0.0216)	(0.0212)		
$I(OneFlood_i) \times LogSBADamage_i$			0.967***	0.972***
			(0.0273)	(0.0290)
$I(OneFlood_i) \times I(LowHistLoss_i)$	0.0129		-0.0617	
	(0.0361)		(0.0432)	
$I(OneFlood_i) \times I(LowGrowth_i)$	0.0742**		-0.00334	
	(0.0343)		(0.0498)	
$I(OneFlood_i) \times I(LowHistLoss_i) \times$				
$\times Northeast$		0.124**		0.0887**
		(0.0570)		(0.0370)
$\times MidAtlantic$		0.0296		-0.0744
		(0.0657)		(0.0728)
$\times Midwest$		0.0640		-0.0277
		(0.0436)		(0.0415)
$\times SouthAtlantic$		-0.0817**		-0.152
		(0.0391)		(0.0929)
$\times SouthCentral$		-0.0383		-0.132**
		(0.0449)		(0.0523)
$\times West$		0.0383		0.0605
		(0.0631)		(0.0736)
$I(OneFlood_i) \times I(LowGrowth_i) \times$				
$\times Northeast$		0.0580		0.137***
		(0.0517)		(0.0414)
$\times MidAtlantic$		0.0940***		-0.0204
		(0.0260)		(0.0841)
$\times Midwest$		0.0139		0.0348
		(0.0563)		(0.0867)
$\times SouthAtlantic$		0.0150		-0.104
		(0.0547)		(0.103)
$\times SouthCentral$		0.145**		-0.0689
		(0.0589)		(0.147)
$\times West$		-0.0904		-0.0394
		(0.0751)		(0.0435)
$I(OneFlood_i) \times$				
Share 100-year Flood Zone	-0.302***	-0.280***	0.121	0.149
	(0.0929)	(0.0958)	(0.0974)	(0.110)
Share 500-year Flood Zone	-0.581***	-0.571***	-0.132	-0.152
	(0.0817)	(0.0790)	(0.124)	(0.128)
Observations	2,851	2,851	2,879	2,879
R-squared	0.980	0.980	0.963	0.964

Notes: *** p<0.01, ** p<0.05, * p<0.1. *FEMA Relief* is the total non-refundable payments by FEMA to cover losses. *SBA Loans* is the total amount of loans to cover damage. *I(OneFlood)* is an indicator for the occurrence of one flood during the sample. *Damage* is total damage per capita. $I(LosHistLoss_i)$ is an indicator for below-median historical loss. *FEMA Damage* refers to total damage per capita reported by FEMA and related to relief payments. *SBA Damage* refers to total damage per capita reported by SBA and related to disaster loans. Additional (non-reported) controls: in (1), (2) *Share Sba Dam/Share Bus Dam*; in (1), (2) *Share Fema Dam/Share Bus Dam*. I have split region 1 into Northeast and Mid-Atlantic and region 3 into South Atlantic and South Central. Sample covers the period between 2000 and 2016. SE clustered by state.

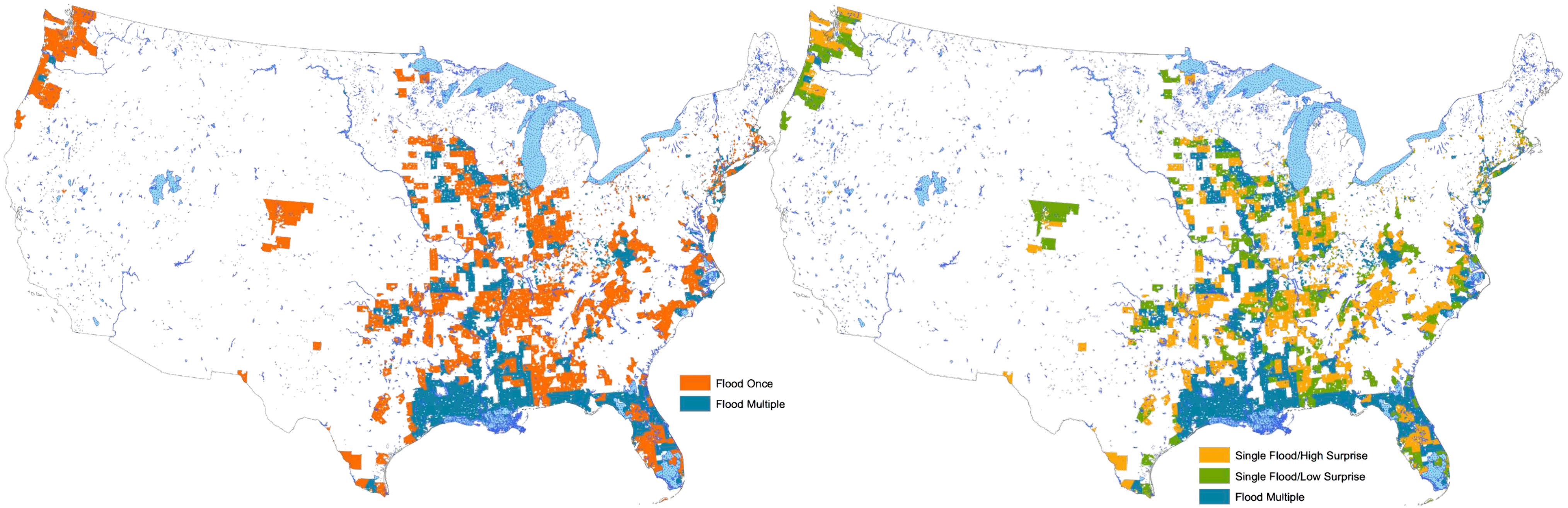

Figure 1: Locations with Flood Surprises between 2003–2013

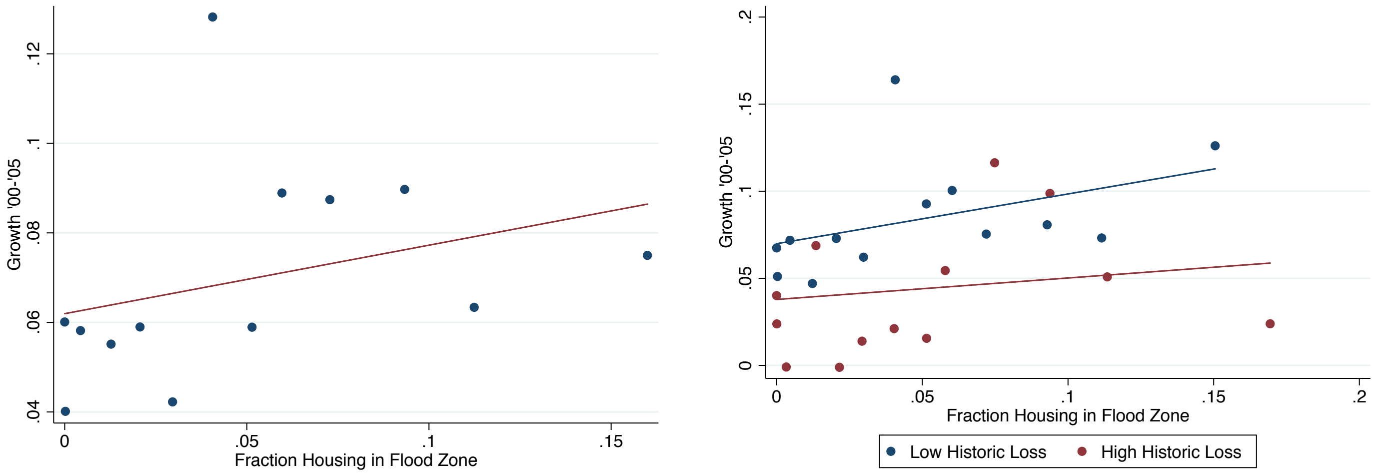

Figure 2: Proximity to Water and Population Growth

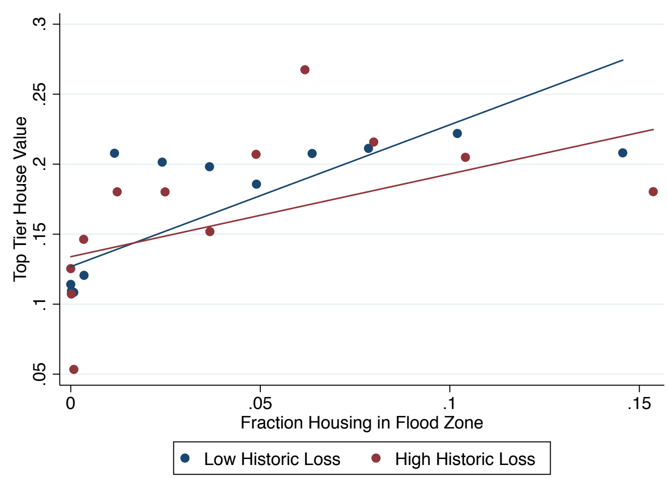

Figure 3: Top Tier House Price and Proximity to Water

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Appendix (for online publication)

Appendix A: Data Construction

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 2 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, due to a change in data reporting. Fraction of population in a flood zone has been calculated by overlaying community flood zones with census blocks from the 2000 Census. I use area as weights to assign the 2000 population from each block to flood zones.

Appendix B: Robustness

Table B1: Communities with Different Flood Frequencies by State

State	Communities with X Floods			
	X=0	X=1	X=2	X>2
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

The table lists the total number of communities which experience one/two/three/more than three floods during the sample years of 2003-2013 for each state. A flood is an event with more than 0.01% total loss as a fraction of the community's real estate value. Two consecutive floods are are placed within the "one-flood" category.