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

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**Abstract**

I provide new evidence about the information content of weather shocks in the US coastal states, based on substantial hurricane impacts, with a quasi-experimental research design that matches counties by risk, size, and income. I examine if hurricanes represent "new news" in counties with no prior hurricanes and if expectations updating is reflected in population and house price growth. I develop a measure reflecting homeowners' flood risk expectation based on flood insurance deductible data, which assumes that higher deductibles reveal lower flood expectations. I find that population growth declines more in counties without previous hurricanes and that this is driven by areas with lower flood-risk priors, consistent with updating when the hurricane is more likely to be "new news". This is supported by within-county evidence that directly controls for hurricane losses and residents' priors. I find that information updating actually increases house price growth in impacted counties with no previous hurricanes.

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# 1 Introduction

There is little consensus about how environmental drivers influence internal migration, particularly in high-income countries (Berlemann and Steinhardt, 2017; Hoffmann et al., 2020).[1] For example, there is evidence of stable population after hurricanes (Deryugina, 2017; Strobl, 2011); of declines in growing (Fussell et al., 2017) or in richer (Logan et al., 2016) counties; of increases in the early 20th century Boustan et al. (2012); and of increased out-migration in a century-long data sample (Boustan et al., 2020). Migration is considered an important adaptation response to environmental change (Hauer, 2017) but our understanding of how it influences vulnerability and resilience is still limited (Black et al., 2011).

I provide new evidence about how population in the US coastal states adjusts after severe hurricane shocks and whether relocations are driven by information updating. Do hurricanes represent "new news" which can update people's prior beliefs (referred as priors) regarding future risk or are they ignored as "flukes of nature"? Since risk updating can change population growth and also be capitalized in house prices, I consider the impact on both and provide a comprehensive evaluation of the information content of weather shocks.

I analyze an original dataset of hurricane losses, during 2000-2019, and investigate the county impact after substantial damage: over 0.66% of county GDP.[2] Based on evidence that most of the economic effect occurs within a year (Belasen and Polachek, 2008; Strobl, 2011; Cortés and Strahan, 2017), I focus on changes in the growth of population and house prices 12 months after the impact. My research design extends the basic difference-in-difference framework by designating quasi-experimental comparison groups that match counties on a set of characteristics (Xiao and Feser, 2014). Past research is clear that public investments Boustan et al. (2012), government transfers Deryugina (2017), pre-existing population trajec-

[1]Most evidence in developed countries is based on case-studies, e.g. Fussell (2015), Vigdor (2008), and Landry et al. (2007), focusing on extreme-loss events which are not representative for the universe of hurricanes (Boustan et al., 2020). There is also significant evidence from developing countries, as discussed in Berlemann and Steinhardt (2017).

[2]This represents about 20% of the counties which experience any hurricane impact. I follow the literature, which focuses on areas with higher impact, approximated with fatalities, wind speed, or using the SHELDUS data. Deryugina (2017), in contrast, uses presidential declarations.

tory Fussell et al. (2017), and income Logan et al. (2016) can amplify or dampen population responses to weather shocks. I identify the impact of hurricanes across counties that are similarly affected by these factors, and represent an appropriate counterfactual.[3] Based on the quasi-experimental setting that groups counties by risk, size, and income, I find that hurricanes reduce population growth by 0.22%, or 17% of standard deviation.

How much of this is due to updating of risk expectations? A disaster may cause people to relocate due to Bayesian updating of the probability of damage or because of loss of sunk cost investments, which reduces the cost of moving relative to staying (Kocornik-Mina et al., 2020). Empirical evidence for learning-driven migration is mixed. Boustan et al. (2012) argues that disaster risk information in the 1920s is limited and disasters in the 30s/40s are "new news" but finds that young men moved into hurricane areas, likely due to the ongoing public flood-control investments, which crowd out private protection. Boustan et al. (2020) examines a similar channel by focusing on the period after 1980, when disasters intensified and new shocks may carry new information, and by using geographical features to predict county risk and identify the responses in low-risk counties as conveying "new news". They only find increases in post-1980 responses to mild events. Kocornik-Mina et al. (2020) study large-scale urban floods in 2003-2008 across 40 countries and focus on newly populated areas with no disaster record. These experience higher reductions in economic activity, consistent with updating only when prior risk information is limited.

To answer the above question, I follow the identification strategy proposed by Boustan et al. (2020) that a natural disaster is "new news" in areas with low underlying risk. I assume that counties with no hurricanes since the 50s are likely to be such places and compare their response to counties with some prior hurricanes. This parallels Kocornik-Mina et al. (2020) to the extent that a history of no hurricanes leads to the same priors as when there is no disaster record. I find that the decline in growth is significantly higher in counties without

[3] For example, the population response of a treated county might be the same as untreated one because the treated county is poorer than the untreated and higher income population is more sensitive to weather losses. This will lead us to conclude erroneously that hurricane strikes do not affect population growth because income confounds the response.

previous hurricanes, consistent with updating when the hurricane is more likely to be "new news". The decline is driven by higher out-migration, not matched by increased in-migration.

I extend the identification strategy with a new proxy for residents' priors.[4] I develop a measure reflecting homeowners' flood risk expectations from data about flood insurance deductibles. It is based on the assumption that those who choose a higher deductible when insuring otherwise similar residences reveal a lower expectation of flood loss.[5] Armed with this, I examine how the population response in counties with no prior hurricanes depends on the revealed risk expectations. I find that counties with lower flood expectations see higher declines in population growth after the hurricane strike, consistent with updating of flood risk. One concern is that counties with lower flood expectations have higher loss to sunk cost investments, leading to higher relocations. This is addressed by the quasi-experimental design that matches counties by risk, size, and income. Since the underlying risk and expected damage is the same across the comparison group, only residents' beliefs are different and not the expected loss.[6] I provide evidence for this in the robustness section.

My final evidence relies on within-county variation, which allows for town and county-year fixed effects that account for permanent differences in risk due to geography and for county-specific responses to the hurricane strike. I use a sample of state-places (referred to as towns) within counties with no history of hurricanes and control both for hurricane losses and flood expectations. This specification partials out the effect of losses of sunk cost investments and identifies the effect of flood expectations as conveying "new news". I find that towns lower prior grow about 40% slower after the hurricane.

House prices within treated no-history counties grow faster in areas with low priors.

[4]The recent literature on the capitalization of sea-level rise in house prices highlights the importance of risk beliefs, for the economic impact of new weather risk information (Bakkensen and Barrage, 2021; Baldauf et al., 2020; Murfin and Spiegel, 2020).

[5]In the empirical specification I divide the difference between the chosen deductible and the minimum deductible by the difference in the chosen premium and the premium with the minimum deductible. Since homeowners can save on the flood insurance premium by choosing a higher deductible, they can choose an above-minimum deductible if their expected risk of flooding, or information prior, is below the (premium-savings)/(additional-deductible-exposure) ratio (Cohen and Einav, 2007).

[6]See (Bakkensen and Barrage, 2021; Baldauf et al., 2020; Murfin and Spiegel, 2020) for why beliefs can differ even with the same weather risk.

Given the population results, this is *not consistent with lower housing demand* after risk revisions, or at least suggests a relatively smaller reduction. Instead, the evidence points to a supply contraction, strong enough to increase price growth even with slower population growth. This suggests that local governments limit construction or enforce zoning more aggressively.[7] The housing evidence implies that population growth declines due to changes in expected risk that indirectly affect the location choice by reducing available housing. This further clarifies that surprises can reshape the population and house prices as a result of measures taken by local communities as expected risk increases.

My main contribution is in distinguishing whether severe hurricanes convey "new news" in counties with limited previous experience with hurricanes. I provide comprehensive evidence for the impact on population and on house prices. First, I find that destruction of sunk investment and learning about weather risk can similarly affect population relocation. In contrast, learning has a minimal impact in areas with previous hurricanes or where severe weather is expected. The learning occurring after hurricanes that break with pre-existing expectations implies that areas subject to surprises can reduce future risk more easily since they internalize new information, while areas that appear less responsive to information shocks will need to depend on major public and private investments or forced resettlements (Hallegatte, 2006; Petkov, 2021). Second, the house price evidence further clarifies how "new news" allow communities to learn about weather risk. My results suggest that expectation revisions are internalized through restrictions in the housing supply, highlighting that hazard mitigation is delivered by the local government (Prater and Lindell, 2000).

This paper contributes to the literature on expectation formation, learning, and adjustment after rare events. There is evidence that perceived weather risk responds to weather extremes (Deryugina, 2013; Cameron and Shah, 2015; Konisky et al., 2016), increases insurance demand (Gallagher, 2014), is capitalized in house prices after disasters (Atreya and Ferreira, 2015; Bin and Landry, 2013; Kousky, 2010) or flood-zone updates (Hino and Burke,

[7] I provide evidence for this in the robustness section.

2021; Indaco et al., 2019), and can lead to relocations (Baker et al., 2009; Boustan et al., 2020; Kocornik-Mina et al., 2020; Röckert and Kraehnert, 2021). As reviewed above, there is very limited evidence of information-driven environmental migration in developed countries but even for developing countries the evidence is mixed (Berlemann and Steinhardt, 2017). My results are consistent with Boustan et al. (2020) in implying that hurricanes can lead to information updating. My contribution is in providing an original dataset of hurricane losses and a novel measure of flood expectations. I show that the hypothesized "new news" effect of hurricanes is empirically relevant once we account for flood expectations. I incorporate a quasi-experimental research design, which can justify the assumption the lower expectations are not confounded by higher losses.

I contribute to the literature of capitalization of environmental risk in house prices. The evidence of post-disaster price decline (listed above) is contested as overlooking damages (Atreya and Ferreira, 2015), or amenity values (Atreya and Czajkowski, 2019; Beltrán et al., 2018). A recent literature on the risk from sea-level rise argues that local weather expectations are key (Bakkensen and Barrage, 2021; Baldauf et al., 2020; Barrage and Furst, 2019; Bernstein et al., 2019; Murfin and Spiegel, 2020). My results that prices increase in areas with lower priors do not confront existing evidence, which focuses on high-risk flood zones, e.g. Hallstrom and Smith (2005); Bin and Landry (2013), but are relevant for studies that find a wide spread price decline after disasters, e.g. Kousky (2010). My evidence is complementary because it shows that there are differences based on the homeowners' priors about risk. Higher surprises may lead to a reduction in supply driven by stricter building standard or flood-zone enforcement. This is likely unique to areas that are newly impacted by hazards, which is not the case for the majority of papers that find a reduction in prices.

The paper proceeds as follows: section 2 describes the data sources and definitions of the main variables of interest; section 3 focuses on the effect of hurricanes on population; section 4 discusses the effect on house values; section 5 includes robustness checks.

# 2 Data, Sample Selection, and Definition of Shocks

This section provides data sources and definitions of the main variables of interest.

**Hurricane Damages and Exposure:** The sample focuses on counties in US coastal states with a hurricane disaster declaration during 2000-2019. I compile hurricane-related losses by adding insured and uninsured damages from four different sources: the Individuals and Households Program grants (IHP); Small Business Administration relief loans (SBA); Public Assistance (PA); National Flood Insurance Program claims (NFIP).[8]

FEMA provides non-repayable grants to homeowners and renters to cover disaster losses (immediate needs following disasters) through the IHP. I use the total property damage from this data source, which is determined by FEMA inspectors and is listed at the town-county level, for each disaster. The SBA dataset of verified residential and business damage is based on applications for low-interest loans to cover uninsured losses. It includes the total loan amount requested, loss incurred, and the location of the property. Losses are listed at the county level for each disaster. Total county losses include both residential and business-related losses from this dataset. The PA dataset includes county-level, disaster-specific damage to roads and bridges, water control facilities, public buildings, and public utilities. I use the total amount of public assistance paid to each county to approximate the amount of damage to the public infrastructure. Finally, I identify the insured loss caused by flooding with NFIP dataset of flood insurance claims. For each claim the data includes the census tract, the amount paid, the date on which the loss was incurred, as well as the characteristics of the structure (flood zone, date built, number of floors, etc.). I match the date of loss to the hurricane date in each county to identify whether the insurance claim is related to a disaster declaration. Additional details are listed in Appendix A

**Flood Insurance:** In addition to the data on flood insurance claims, I use information

[8] The IHP, PA, and NFIP data is hosted on FEMA's website. The SBA data is available on SBA's website. Losses exclude *insured* wind losses, which are partially covered by home-owner's insurance, or vehicle losses. A recent CBO report (CBO (2019)) approximately 60% of annual damage is due to flooding, which suggests that my estimate of losses captures a big portion of actual losses.

on the number of purchased flood insurance policies. I use this data to build a proxy for residents' flood risk expectations. It is available on FEMA's website and provides all of the building characteristics necessary to determine the premium (or insurance policy cost) paid by each homeowner. This data lists the census tract of each insured property and allows me to identify what deductibles are chosen by homeowners at the county level, and at the more granular town/tract level. Premiums depend on the flood zone, building elevation, amount covered, date of construction, and the size of the deductible. For pre-1974 flood zone structures premiums are based on coverage, for the rest they are based on the elevation relative to the 1%-a-year flood BFE.[9] Flood insurance is required for mortgaged structures in the 100-year zone, where flooding of a specified elevation (BFE) can occur with an annual probability of 1%.[10] This ensures that each county with an established flood zone will have information about the number of existing flood insurance policies and the deductibles chosen by residents. The latter is key for my measure of flood risk expectations. The policy data starts from 2008 but includes the initial year of purchase for all active policies. For policies prior to 2008, I use the date of initial purchase to reconstruct earlier insurance data. In the robustness section, I examine the sensitivity of the main results using only post-2008 insurance policy information.

**Flood Expectations and Surprises:** The research design in this study focuses on counties with low weather risk expectations and assumes that hurricane strikes are more likely to be "new news" in such areas. I identify areas with low expectations in two ways: using hurricane history before 2000 and using a novel measure of flood risk expectations based on flood insurance deductibles. For the first measure, I use historical county data from FEMA about hurricane-related disaster declarations. For the second measure, I use deductibles data from the FEMA dataset on active flood insurance policies.

The logic of the flood risk expectations measure, based on insurance data, is that home-

[9]Numbers are based on the pre-2010 insurance cost. Generally, pre-1974 structures have higher premiums compared to post-1974 ones, which tend to be elevated: $1,000 vs. $600.

[10]Kousky (2018) provides an in-depth discussion of the NFIP.

owners who consider weather risk unlikely will choose a relatively high deductible in order to reduce the cost of insurance (premium). The cost of insurance is lower with higher deductible because it limits the insurance payout in the case of flooding. Switching from $1,000 to $2,000 in building deductible reduces the premium by 5%, or $25 with $500 premium. The $25 saving trades off an increase in out-of-pocket cost of $1,000 in the case of flooding. If a risk-neutral resident expects the risk of incurring an additional $1,000 is less than 2.5% they choose the higher deductible. By comparing the difference in the premium to the difference in deductible we can determine the risk of flooding assumed by a homeowner who chooses an above-minimum deductible.

I calculate what I refer to as upper bound of expected probability of low-damage flood by focusing on homeowners who have chosen above minimum deductible.[11] For each, I calculate the change in the premium if the homeowner were to choose the minimum deductible and the change in the deductible from their current higher deductible to the minimum deductible. The ratio of the premium change relative to the deductible change gives the upper bound of expected risk of flooding, as showcased in the example above.

I calculate what I refer to as a lower bound of expected probability of low-damage flood by focusing on homeowners who have chosen the minimum-deductible option. For those, I divide the decrease in the premium from choosing a higher deductible by the increase in out-of-pocket exposure. More specifically, I compare the deductible/premium at the minimum-deductible option and at the next-to-minimum deductible option. Prior to 2010 the minimum was $500/$500 and next-to-minimum was $1,000/$500. Post 2010, the minimum is $1,000/$1,000 and the next-to-minimum is $2,000/$1,000.

I use the average of the upper and lower bound as the second proxy of expectations. I aggregate individual expectations by taking the average by the county or town/census tract. I multiply all expectations measures by -1 to represent the level of surprise after

[11] I consider residents who take at most $4,000 of combined (building and contents) deductible prior to 2010 and at most $6,000 afterwards. Following 2010, the minimum possible deductible increased from a combined $1,000 to $2,000.

an event, i.e. an increase reflects a lower expected risk and hence a higher surprise in the case of a hurricane. I also use the residuals from regressing the upper/lower bound on the characteristics of the insured structure. For more details consult Appendix A.

In order to calculate how the premium of each insurance policy will change if the homeowner were to choose a different deductible I use the stated housing characteristics such as flood zone, building elevation, amount covered, date of construction. I use the information from the NFIP's flood insurance manual (available on FEMA's website) which details the relationship between the premium and deductible, conditional on the housing characteristics. The handbook describes the "premium factor" for different deductibles based on the date of construction, flood zone, building elevation, etc. For more information and an example of a table of premium factors from the NFIP's flood insurance manual, refer to Appendix A.

**County Peer Groups**: I define two county groups using different definitions of risk and interact each with income and population categories in order to limit the role county unobservables which can confound population growth. For the first, I model the risk of having over 0.66% damage with a probit regression of actual 0.66%+ damage on a set of housing characteristics and split the predicted values into 15 categories.[12] The second is based on the fraction of housing in high-risk flood zones interacted with historical hurricane incidence.[13]

**Population, Migration, House Prices, and Income**: Annual population/buildings estimates come from the Census. Migration comes from the IRS data. I also use tract USPS quarterly addresses data.[14] Census tract house values are based on the House Price Index (HPI) from the FHFA, which measures newly-sold single-family prices changes, controlling for time-invariant unobservable effects. I also use Zillow's town-level House Value Index,

[12]The regressors are: fraction in high-risk flood zone, fraction in low-risk flood zone, fraction built before 1974, fraction elevated, fraction 3+ floors, fraction town-houses, fraction in communities with 7+ on the Community Rating System, fraction non-primary residences, indicator for no pre'00 hurricane declarations, average building insurance coverage.

[13]Population groups are based on cutoffs at 10,000 and 100,000. Income per capita groups are based on cutoffs at $20,000 and $40,000. Flood-zone groups are based on the deciles of the distribution. The hurricane incidence groups are defined as no-hurricane pre'00 and some hurricanes pre'00.

[14]It USPS data starts from the end of 2005. I subtract the number of non-deliverable addresses (known as non-stat) from the total mailing addresses and use this adjusted measure to identify annual population changes at the census tract.

which represents the median quality-adjusted house values. County income is from the Bureau of Economic Analysis (BEA) coving 2000 to 2018.

**Sample Selection and Summary Statistics**: The sample includes the year before/after each hurricane during 2000-2019 for counties in US coastal states with hurricane-related disaster declarations, designating those with 0.66%+ damage as treated. In the robustness section I lower the damage definition of treatment to 0.33%+. The included states are: Alabama, Florida, Georgia, Louisiana, Maryland, Mississippi, North Carolina, New Jersey, New York, Pennsylvania, Texas, Virginia. You can also find the list and summary statistics for each state in Table 3. Hurricanes occur in late August/early September and population is reported end of June. Population in June of the hurricane year is pre- and in the following year is post-event.[15] I drop counties with over 50% damage.

# 3 Expectations Revisions and Losses After Hurricanes: Impact on Population

This section discusses the identification strategy, empirical model, and estimates related to the effect of hurricane-generated surprises on population growth and migration. It presents the county-level composite effect, the heterogeneous effect by hurricane history and by residents' deductible-inferred expected flood probability, and the within-county – town or census tract – effect with joint damage and expectations controls.

## 3.1 Descriptive Evidence

Counties with hurricane declarations attract more population and are riskier: they grow faster than the average, have more flood-zone buildings and lower flood expectations, according to Table 1. Relative to counties with declarations, the 0.66%+ ones are bigger, are

[15]If the hurricane occurs before June, the pre-year is the year before the hurricane and the post-year is the year of the hurricane. One exception to this is the migration and HPI data which covers the entire year. In this case the pre- year is the one that precedes the hurricane and the post- year is the year of the hurricane.

exposed to flood risk, and have lower flood expectations. The effect of hurricanes is evident form simple average comparisons. Being impacted by a hurricane (treated) reduces the county population growth by close to 0.3%, or 0.545% vs 0.257%. This difference is stronger when places have limited historical experience with hurricanes.

The empirical model distinguishes pre-hurricane expectations, either with historical experience or the implicit probability of flooding from deductibles, to quantify the role of surprises in places with hurricanes. To build intuition, Table 2 lists regression estimates of the implicit expectations from deductibles on individual or county factors. Lower expectations are associated with lower susceptibility due to recent construction and elevated or low-risk flood-zone structures. Table 3 presents the state distribution of expectations, multiplied by -1 to reflect surprises. Hurricane history does not fully capture surprises: expectations are lower with hurricane experience compared to without in 5 of 11, suggesting that previous events lead to adaptions that reduce (perceived) risk. I account for this when selecting county peer groups.

Table 4 lists summary statistics for locations within treated counties by historical hurricanes. Population growth is negative after the first hurricane and is positive with pre-sample hurricanes. State-places with surprises have limited historical experience but not all of them have low loss expectations: those with and without pre-sample hurricanes have similar average surprise, but the latter have substantially higher standard deviation. All tracts experience similar losses, measured by the fraction of claimed insurance, but those with no pre-sample hurricanes have higher surprise.

## 3.2 Overview of Approaches

The empirical model identifies the short-run population growth response in the year after a hurricane *relative to the pre-hurricane year and to other counties within a peer group with similar characteristics.*[16] To capture the independent effect due to potential expectation revision after a hurricane, I pursue three different approaches. First, I start with the het-

[16]The shorter span helps simplify the treatment of long-term trends over the twenty-year sample and the potential feedback from hurricane loss.

erogeneity across locations with different historical experience. Hurricane history reflects resident expectations only partially, since learning can occur indirectly, e.g. neighbors can update expectations. To allow for this, in the second approach, I use flood probability inferred from deductibles. I identify information shocks to the the location choice with growth difference in places with different pre-existing expectations, assuming that de-facto losses do not vary with pre-existing expectations, *within* the peer group.

The effect heterogeneity can reflect a combination of physical susceptibility, or vulnerability, and changes in severe-weather expectations (Keating et al., 2014). To disentangle each, in the third approach, I estimate a within-county model that controls for direct loss and pre-existing expectations and examine growth at towns or tracts with similar damage but different expectations. I interpret growth differences as location choice shocks that hold de-facto damage constant and reflect adjustments in expectations.

## 3.3 Composite Effect of Hurricanes

### 3.3.1 Empirical Methodology

The model of the unconditional effect of hurricanes, using the year pre/post a hurricane for counties with declarations during 2000-2019, is:

$$\triangle \ln \mathrm{Pop}_{c,t} = \beta \mathrm{Hur}_{c,t-1} + \alpha_c + \psi_{PeerGroup(c),t} + \epsilon_{c,t} \tag{1}$$

$\triangle \ln \mathrm{Pop}_{c,t}$ is annual population log difference in county $c$, year $t$. $\mathrm{Hur}_{c,t-1}$ is the treatment lag (0.66%+ damage). $\alpha_c/\psi_{PeerGroup(c),t}$ are county/peer-group-year FEs. $\beta$ is the composite hurricane growth impact, driven by: losses to private, public or commercial property or expectations adjustments, which are key in the rebuilding/location decision.[17] The model cannot distinguish individual factors but provides a test for the average impact.

The county FE allows for non-parametric growth differences due to invariant factors. The peer-group-year FE controls for common time-varying shocks. In contrast to the existing

[17]More resilient structures are significantly more expensive and limit the number of people that can afford to live in the community.

literature, which assumes that hurricanes are random within states and uses unaffected counties as a control group (Strobl, 2011), I use declaration counties with loss below 0.66% as controls. $\beta$ is identified as the composite hurricane effect, assuming that treated and untreated counties are not qualitatively different. This can be violated if untreated counties are better at limiting losses. If treatment depends on risk, income, or population, $\beta$ will reflect the joint impact. Peer groups FEs mitigate this since the effect is estimated relative to similar counties. I build county risk groups using: i) predicted probability of 0.66%+ damage from a probit model; ii) state decile of the fraction of flood-zone housing interacted with hurricane history.[18] Allowing for common shocks across counties with similar risk helps estimate $\beta$ holding expected loss, or risk, constant. I interact risk groups with population and income categories, resulting in groups with similar risk, size, and development.

### 3.3.2 Results

Estimates with different control groups are in Table 5, columns (1)-(6). With a state-year FE, growth falls by 0.18% post hurricane. The effect is slightly stronger when including a risk-group FE in (2), which compares population responses across counties with similar risk. It increases substantially with population/income FE, in (3) and (4), underscoring that responses depend on the relative size and income.[19] With FEs for all three peer-group controls, growth declines by 0.22%. The estimated decline is 0.25% when county risk is based on the decile of high-risk flood zone structures and a hurricane history indicator. The difference seems to be due to the faster growth at counties with some hurricane history. Hurricanes reduce growth close to 17% of standard deviation. The result is robust to several alternative specifications of the control group and has the highest magnitude when counties

[18]More specifically, I construct such a group by estimating the ex-post county probability of having damage over 0.66% based on the lagged county average of fraction of residences that are in high-risk flood zone, in low-risk flood zone, built before 1974, elevated, 3+ floors, town-houses, in communities with 7+ on the Community Rating System, non-primary residences. I also control for an indicator for no pre-sample hurricane declarations and for the average building insurance coverage. The regressors are based on the data on active flood insurance policies.

[19]Population size has three categories relative to cutoffs at 10,000 and 100,000 people. Income-per-capita category is based on cutoffs at $20,000 and $40,000.

are matched by risk, size, and economic development. Growth declines due to a combination of displacement during the recovery and changes in expectations that discourage rebuilding or cause residents to relocate. Next, I decompose the role of each, assuming that places with lower pre-existing expectations experience stronger information shocks and by proxying for expectations with historical experience or insurance deductibles.

## 3.4 Differences by Historical Hurricane Incidence

### 3.4.1 Empirical Methodology

The composite effect reflects: i) current property loss, business interruption, and duration of recovery; ii) changes in expectations of future loss. The second factor can be limited in places with a long – and frequent – history of hazards, which is key in quantifying the importance of expectations elsewhere. I distinguish two county groups: with zero hurricane declarations and with some declarations, going back to 1950. Comparing growth after a hurricane in the first group *relative* to the second identifies the additional impact of adjusting expectations. This interpretation requires that counties are otherwise similar – likely to be the case within the peer-group-year FE which controls for the probability of a weather event, income, and population.[20] Controlling for the pre-existing physical characteristics, via weather risk, is critical to make sure that actual losses are similar. The formal model, using population growth and migration is:

$$\triangle \ln \text{Pop}_{c,t} = \beta_1 \text{Hur}_{c,t-1} \text{NoHist}_c + \beta_2 \text{Hur}_{c,t-1} \text{YesHist}_c + \alpha_c + \psi_{PeerGroup(c),t} + \epsilon_{c,t} \qquad (2)$$

$\text{Hur}_{c,t-1}$ depends on declarations during 1950-2000: $\text{NoHist}_c/\text{YesHist}_c$ are indicators for no/some declarations. $\beta_1$ and $\beta_2$ are expected to be negative, reflecting a short-term growth decline due to a combination of property loss and expectations, causing some to reconsider their location choice. The coefficients are identified by comparing growth in treated counties relative to the untreated, within a group with the same income, population, and predicted

[20] Note that I use physical characteristics to predict the likelihood of a hurricane causing 0.66%+ loss. Groups based on this will match counties with similar risk factors. This does not imply that residents will have similar expectations about the underlying weather risk.

probability of having over 0.66% loss. If all treated counties have similar losses, which result in similar population responses, but different pre-existing expectations, the difference in coefficients captures the the role of surprise after the impact due to revisions. This relies on counties which differ by history but otherwise have similar predicted probability of 0.66%+ loss from the probit model. When I model risk with the flood-zone building share, I also interact with hurricane history, which changes the identification strategy. In this case, I compare treated counties with no hurricane history to untreated ones also without history but similar flood-zone shares – likewise for counties with hurricane history. With this strategy, growth differences across treated and untreated counties with no hurricane history capture the effect of losses and *relative* adjustment in expectations. The same comparison across counties with some hurricane history should reflect mostly the effect of losses since expectations are assumed to be stable and do not respond to treatment. In all cases, comparing the two coefficients quantifies the role of expectation revisions in no-history counties.

### 3.4.2 Results

The results by hurricane history are in Table 5, columns (7)-(8), using two risk specifications. In the first, growth declines by 0.4% (30% of s.d.) in the no-history counties compared to 0.16% (11% of s.d.) decline elsewhere. If the pure damage effect is identified by the some-history counties then the growth impact of the information shock makes up 60%. In the second, declines are similar but significant only in the counties with history (0.28%), suggesting a minimal information impact. The evidence confirms that hurricanes depress growth in all treated counties and highlights an important source of heterogeneity: prior hurricanes experience. Assuming that losses do not vary by history and that expectations are stable in places with prior experience, the stronger decline in (7) for counties with no prior hurricanes can be attributed to expectation revisions. The similar decline, in (8), which compares treated to untreated counties with no history, suggests that the role of expectations is smaller. This is due to the fact that not all no-history counties have low pre-existing expectations and/or expectations can adjust significantly in the no-history control group. I address this directly in the next section by controlling for the level of pre-existing expectations in all no-history counties.

Expectation revisions can slow down the arrival of new residents or incentivize the relocation of existing ones. The migration impact estimates suggest that residents are moving out 3.7%/3.3% faster relative to the peer untreated counties. The effect is robust to risk group specifications and the magnitude is consistent with the population growth estimate. Counties with hurricane history do not experience such outflows but instead see slightly lower inflows. Assuming stable expectations in some-history counties suggests that 100% of outflows are driven by the information shock. The migrations estimates reveal an important aspect of risk revisions that cannot be identified from population growth: they can lead to sorting as residents who reduce potential exposure are replaced by those who tolerate higher risk (Bakkensen and Barrage, 2021). This is evident from (8) and (12) where growth declines less due to somewhat higher inflow. The results are consistent with the interpretation that residents of counties with prior hurricanes have stable expectations, only potential new residents appear to update theirs, leading to lower growth. The risk FE matches counties likely to experience a similar impact when treated, reducing the concern of damage difference. This supports the interpretation that expectations adjustments can meaningfully impact growth in addition to property loss.

## 3.5 Differences by County-level Flood Surprises

### 3.5.1 Empirical Methodology

Communities are exposed to new information from neighbors and can be subject to low-damage, expectations-updating events, and not all locations with limited historical incidence exhibit an expectations shock. To more directly focus on pre-existing expectations, I measure surprise with the inverse of the expectation of low-impact flooding from insurance deductibles. The growth response in counties with low expectations *after* a hurricane can reveal the role of adjustments in expectations resulting from surprises. Gallagher (2014) describes that insurance take-up picks up after extreme weather and slowly diminishes over time. A similar learning process will lead to updating right after a hurricane, generating a *bigger* proportional adjustment in counties with *lower* pre-existing expectations, and, as a result, a stronger growth response.

The identification strategy compares counties with no hurricane history where residents chose a higher deductible only for substantial premium savings, or have higher pre-existing expectations, to those who do so even for smaller savings, or have lower pre-existing expectations, with the model:

$$\begin{aligned}\triangle \ln \text{Pop}_{c,t} = {} & \beta_3 \text{Hur}_{c,t-1}\text{NoHist}_c + \beta_4 \text{Hur}_{c,t-1}\text{NoHist}_c \times \text{Surprise}_{c,t-1} + \beta_5 \text{NoHist}_c \\ & \times \text{Surprise}_{c,t-1} + \beta_6 \text{Hur}_{c,t-1}\text{YesHist}_c + \beta_7 \text{Hur}_{c,t-1}\text{YesHist}_c \\ & \times \text{Surprise}_{c,t-1} + \beta_8 \text{YesHist}_c \times \text{Surprise}_{c,t-1} + \alpha_c + \psi_{PeerGroup(c),t} + \epsilon_{c,t}\end{aligned} \tag{3}$$

where $\text{Surprise}_{c,t-1}$ is the continuous surprise measure.[21] The interaction of pre-existing expectations with treatment in counties with no previous hurricane incidence is estimated with a triple-difference that compares the impact at no-history counties at different levels of pre-existing expectations. In other words, it examines how the estimate from the previous section varies by the surprise measure. The coefficient of interest, $\beta_4$, captures the impact of a higher surprise for treated counties with no hurricane history. A negative estimate implies that treated no-history counties have a higher growth decline when residents assume a lower probability of flood damage, consistent with a surprise that leads to additional growth decline, more significant in counties with lower pre-existing expectations. $\beta_3$ reflects the growth effect for counties where damage is completely unexpected. $\beta_5/\beta_8$ capture the effect of expectations at untreated counties.

There are still two different identification strategies depending on how I model weather risk. When I use a risk group based on the probit predicted probability of 0.66%+ loss,

[21] In the case of the Adjusted Surprise measure, which is based on residuals from regressing observable characteristics, the measure can take positive and negative values and increases still represent higher levels of surprise.

I compare treated no-history counties with different pre-existing expectations to untreated counties with similar predicted probability of loss. When I use the share of flood-zone housing, I compare treated no-history counties with different pre-existing expectations to other no-history untreated counties with similar share of at-risk housing. In the latter case, examining the variation by expectations is critical since no-history counties can vary significantly by hurricane expectations depending on their proximity to previous hurricanes.

### 3.5.2 Results

Estimates in Table 9, distinguish counties by the implicit expectations inferred from the insurance deductible choice. Growth declines by approximately 1% when the upper-bound surprise measure is at its highest. A 5% higher surprise, or lower expected probability of flooding prior to the hurricane, reduces growth by .25% – .5%, depending on the specification of the risk group in (2) or (3). The bottom of Table 9 quantifies the effect at the 25th/75th percentiles: growth is lower by 0.67%/0.46% at high/low surprise counties, relative to the untreated in column (2). With peer groups that include only no-history counties the difference by surprise is even bigger – 0.58%/0.27%. This implies that the information shock reduces growth by 0.2% to 0.3% or about 50% of the total, which is consistent with the previous section.

The stronger growth response with higher surprise remains the case across different proxies: average of the upper/lower bound of expectations; adjusted versions, using the residuals from each of the measures after controlling for insurance policy observables. With the first, the marginal effect of a surprise increase slightly: growth declines by 0.35%/0.66% in counties with 5% higher level of surprise. With the second, the marginal effect is even higher.

The pattern suggests that the surprise reflected in hurricane history underestimates the role of information shocks. The average effects I estimated above is in line with counties at the 25th percentile of surprise. Those with much higher surprise, or lower expectations, reduce growth dramatically more, or about 50% more, than the rest. What explains this? Table 2 provided some of the intuition about which counties have lower expectations and, respectively higher surprise after an impact: places with newer construction, more buildings in low-risk zones, less buildings in high-risk zones, lower coverage, among others. In other words, counties that are presumably safer exhibit the strongest decline in growth after a hurricane, while counties that generally are more at risk do not. Growth declines due to direct losses or changes in expectations of future losses, which can either cause relocations, implementation of mitigation projects, stricter flood-zone management, or increased insurance cost. Direct loss is unlikely to increase with surprise becuase identification is relative to counties with similar risk characteristics.

## 3.6 Differences at Town/Tracts Within No-Hurricane Counties

### 3.6.1 Empirical Methodology

I address the possible correlation between expectations and damage, and identify the role of expectations in locations within affected counties that do not suffer direct damages. I use two samples within 0.66%+ counties, controlling for property loss and pre-existing expectations: i) towns or state-places, using population growth; ii) census tracts, using mailing addresses growth. The damage proxy is the fraction of claimed flood insurance. Surprise is similar to the county measure, but is aggregated at the town or census tract.[22] The formal model is:

$$\triangle \ln \mathrm{Pop}_{l,t} = \gamma_1 \mathrm{Impact}_{l,t-1}^{NoHist} + \gamma_2 \mathrm{Suprise}_{l,t-1}^{NoHist} + \zeta \mathrm{Z}_{l,t-1} + \alpha_l + \psi_{c(l),t} + \epsilon_{l,t} \tag{4}$$

$\triangle \ln \mathrm{Pop}_{l,t}$ is the log population difference in $l$: town or census tract. $\mathrm{Impact}_{l,t-1}^{NoHist}$/ $\mathrm{Suprise}_{l,t-1}^{NoHist}$ is the fraction of flood insurance claims/level of surprise in a county with 0.66%+ damage and no pre-sample hurricanes. $\mathrm{Z}_{l,t-1}$ has additional controls, including losses recorded by FEMA inspectors.[23] $\alpha_l$, the location FE, controls for permanent growth

[22] Note that losses and expectations are derived from the flood insurance data. Towns with losses have an associated surprise measure. Other sources of loss will not be reflected in the sample and will not be associated with any level of surprise.

[23] I include fraction in high-/low-risk flood zone, fraction built before 1974, fraction elevated/3+ floors/town-houses/with basement, fraction in communities with 7+ on the Community Rating System, fraction non-primary residences, average building insurance coverage, deductible as a fraction of building coverage.

differences. $\psi_{c(l),t}$, the county/state-place-year FE, controls for common county-level or town-level responses after a hurricane, such as due to different riskiness, income, or population.

$\gamma_1$, the growth effect of direct loss, is identified by comparing towns within the county or tracts within towns, holding pre-existing expectations constant. $\gamma_2$, the effect of expectations, is similarly identified, holding losses constant. In the current setting, $\gamma_2$ reflects the independent effect of pre-existing expectations on population growth. It can be interpreted as the difference in growth across locations that experience the same loss but have different expectations prior to the loss. I also test whether the effect of expectations depends on the impact by interacting the two. Identification in this model differs significantly since I compare town growth relative to the county average or census growth relative to the town average in no-history treated counties. While I can no longer use peer groups to control for risk, I rely on controls in $Z_{l,t-1}$ to limit any confounding impact.

### 3.6.2 Results

The first part of Table 7 focuses on growth at towns within counties with no prior hurricanes and the second uses census-tract growth. Town evidence shows that both losses and surprise reduce growth. In column (1), 25% more losses leads to 0.33% slower growth; 5% higher surprise reduces growth by 0.1%. The bottom panel reports growth at zero loss and the 25th/75th percentiles of flood surprise.[24] Regardless of expectations, no-loss towns grow faster than the rest due to the limited direct impact. Conversely, higher loss reduces town growth, holding expectations constant. At the same time, towns with higher surprise grow about 40% slower *relative* to those with lower surprise: 0.07% versus 0.166%. Column (3) replaces the continuous variables with indicators for the top quartile. Across towns with low losses, those with low expectations grow 0.23% slower *relative* to the rest, post hurricane. In (2), I test the non-linearity of surprise at different loss levels and find that interaction is positive and significant, implying that expectations do not play a role in towns with higher

[24] Note that since the surprise measure is negative, low surprise corresponds to a higher absolute value. The 25th/75th percentile is low/high surprise.

damage but are associated with significant declines elsewhere. With the interaction, the effect of surprise on growth at low-loss towns is amplified: 0.374% versus 0.175%. This is confirmed in (4) with indicators.

Columns (5)-(8) focus on census tracts within the same counties as (1)-(4), using within town variation to identify the main effect.[25] In (5), the effect of surprise is negative and statistically significant, while the loss estimate is negative but not significant. This implies that within-town expectations difference are associated with census tract growth while loss difference are not. Tracts with lower expectations prior to the hurricane, or higher surprise, underperform the rest even after controlling for losses: 5% higher flood surprise is associated with 0.44% lower growth. At low impact, high surprise tracts grow at 0.25% versus 0.9% at low surprise (relative to the town). Column (6) includes an interaction term, which reveals that expectations matter less with higher losses. The magnitude of the interaction leads to different conclusions relative to (2). With towns, expectation differences are not important when losses are higher but matter at lower losses; with tracts within towns, expectations dominate growth outcomes – high surprise tracts grow significantly slower.

## 3.7 Discussion

Altogether, the results suggest that direct damage and surprises, or information shocks, associated with lower pre-existing flood expectations both have an effect of similar magnitude on growth after a hurricane. Property damage reduces growth since structures are either not rebuilt or construction takes a long time. Interestingly, once a community suffers loss it is rebuilt regardless of how surprising the impact is: towns with a high impact experience similar growth regardless of expectations. In contrast, towns with limited damage and low pre-existing expectations experience a growth decline due to information updating. I interpret the occurrence of a hurricane in such towns as an information shock that leads to changes in the location choice for current and future residents. The fact that the decline

[25] The sample starts in 2006.

is stronger in places with lower pre-existing expectation suggests that revisions are more significant with bigger surprises. Towns with higher pre-existing expectations and limited damage appear to be least affected. This suggests that they either have limited revision in expectations or revisions increase the cost of insurance and lower the value of housing, keeping population stable.[26]

## 4 Expectations Revisions and Losses After Hurricanes: the House Price Impact

The evidence so far clearly indicates that surprises due to lower pre-existing expectations are associated with slower growth, particularly if residents have limited direct losses. Growth in low-surprise areas does not respond significantly since pre-existing expectations are stable. This is consistent with the interpretation that high-surprise places experience information shocks to their location, choice causing residents to leave. With sizable losses expectations do not seem to play a role as the effect of loss-driven displacement tends to dominate.

Not all adjustments will be reflected in the relative size of the county or town. Surprises can, instead, affect the going price of real estate as residents who avoid higher-than-anticipated risk sell their property. Revisions of expectations can also lead to significant supply reductions in communities that restrict construction in high-risk areas by implementing stricter regulation. This section helps distinguish whether places that internalize higher weather risk experience demand-driven changes in the housing market, which can dampen the growth impact by attracting new residents with lower prices, or take measures to limit future risk by restricting new construction.

[26]Increasing insurance coverage in locations with higher pre-existing expectations is more expensive. As shown in Table 2 such areas have older, less elevated housing, in higher-risk flood zones.

## 4.1 Empirical Methodology

The setup closely follows the population model, focusing on within county differences – at the town and census tract level. I control jointly for expectations and damage, identifying the role of surprises due to low pre-existing expectation in locations within affected counties that suffer various degrees of direct damages. There are two different samples within 0.66%+ counties: i) towns or state-places, using Zillow's HVI growth; ii) census tracts, using growth in FHFA's HPI. Impact and surprise are proxied as in the population model by flood insurance claims and deductible-based flood probabilities.

There are some important distinctions in the interpretation of what shocks are identified when applying the previous model to the real estate market. Since direct losses and surprises can affect both the supply and demand of housing, estimates should be interpreted in the light of what happens to population and according to whether supply or demand is shifting. With constant supply, the increase in expected risk in surprise locations – which experience slower population growth – is expected to further lower house prices *relative* to places where risk expectations are stable and population is less affected. With contracting supply, higher expected risk can results in a variety of price changes relative to places with stable expectations. A strong contraction in surprise places can increase prices compared to non-surprise places, even with slower population growth.[27] What can cause such supply contractions? Direct property loss can reduce the available housing. Alternatively, local governments can impose stricter building regulations as a result of higher risk expectations. This can reduce the availability of new housing by making new construction more expensive or by instituting no-building zones. Since surprise places are generally less susceptible to damage it is less likely that supply is reduced due to direct losses. I formally examine the house price response with the following model:

$$\triangle \ln \text{HouseIndex}_{l,c,t} = \gamma_1 \text{Impact}^{NoHist}_{l,c,t-1} + \gamma_2 \text{Suprise}^{NoHist}_{l,c,t-1} + \zeta \text{Z}_{l,c,t} + \alpha_l + \psi_{c(l),t} + \epsilon_{l,c,t} \quad (5)$$

[27] I do not discuss the case where the supply in low-surprise places contracts more since expectations are assumed to be stable.

where $\triangle \ln \text{HouseIndex}_{l,c,t}$ is the annual difference the house value index in location $l$, in affected county $c$, during the year $t$. The rest of the variables are defined as in model (4). The coefficient of interest, $\gamma_2$, captures the difference in the growth of house values across locations with different levels of surprise after a hurricane, holding the level of direct hurricane impact constant. A negative estimate is consistent with a demand shock following an increase in risk expectations in places with higher surprise and a limited change in the supple of housing. Residents reduce exposure to higher weather risk by relocating and selling existing property at a lower price that offsets higher risk. This suggests that the population growth responses are actually attenuated by the house price dynamic (Glaeser and Gyourko, 2005). A positive estimate is consistent with the slower population growth evidence only if the housing supply contracts more in high-surprise places relative to the rest. This evidence supports the interpretation of surprises as information shocks but suggests that higher expected risk can trigger local responses to limit future losses that result in lower house supply. A positive estimate implies that local measures ultimately countervail the effect of any reduction in demand due to higher expected risk.

## 4.2 Results

The estimates based on town HVI are listed in the first part of Table 8 and tract-level HPI are listed in the second part. Town evidence from (1) shows that the surprise effect is positive and significant: a 5% higher surprise is increases growth by 0.25%. The bottom panel provides expected growth at low/high surprise and limited property impact: growth in high surprise places is 0.26% below the county average compared to 0.68% below for low-surprise places. The evidence is confirmed in (3) which uses indicators: house values at high-surprise places grow 0.59% faster than low-surprise places. Estimates from specifications that allow for non-linearity are not conclusive and suggest that the effect of surprises does not vary with the level of damage. Column (4) suggests that high-surprise places experience faster growth. The effect of a direct impact is positive and marginally significant, implying that higher losses increase price growth.

Tract evidence from (5)-(8) provides similar predicted values but the estimates are generally not significant. Predicted values from (5) suggest that high-surprise tracts have higher house price growth, 0.18% below the town average, compared to low-surprise tracts, 0.71% below the average. Both estimates are not significant. Results from (7), using indicators imply that prices grow slower in high-impact places and surprises are not important in explaining within-town differences. Column (8) is consistent with the town results, showing that prices grow faster at low surprise tracts.

The evidence across the two samples provides a slightly mixed picture, particularly with the tract-level HPI data. The estimates suggest that house prices generally grow faster in locations that experience surprises due to lower pre-hurricane expectations. In the light of the population results in the previous section, this is *not* consistent with a reduction in the demand for housing after adjustment in risk expectations, or at least suggests a relatively smaller reduction. Instead, the evidence points to a reduction in the supply of housing which is strong enough to lead to faster house-price growth even with slower population growth. Such contraction is unlikely to result from higher loss of property since high surprise places are generally less risky. Alternatively, this can be due to measures by local governments to limit future exposure such as more aggressive enforcement of flood zone regulations or the instituting of no-building zones. Each can limit the housing supply and lead to relatively fast price growth. Since such local measures reflect changes in expected risk, they support the interpretation of surprises as information shocks. They further suggest that the slower population growth is a consequence of changes in expected risk that indirectly affect the location choice by changing the amount of available housing and/or its price.

## 4.3 Discussion

Altogether, the house-price evidence complements the population results in two important ways. It supports the interpretation that adjustments in expectations play a key role in high-surprise areas and prices adjustments are an important indication that high-surprise places are impacted. Interestingly, it further clarifies that surprises can reshape the relative size and house prices as a result of measures taken by local communities as expected risk increases. This interpretation is at odds with the traditional view of self-selecting migration in the case of places with lower pre-hurricane expectations.

# 5 Robustness

This section extends some of the main results and examines their sensitivity.

**Hurricane Losses and Surprise**: A critical identification assumption in the main results is that the measure of flood surprise does not vary with the losses experienced by counties with no previous hurricanes. In other words, I assume that counties with lower flood risk prior are not more likely to experience a higher level of damage. I provide additional evidence for this in Table 9. The results show two different specifications: (1)-(3) regress the surprise measure on hurricane losses, (4)-(6) allows surprise to vary by hurricane history. In all cases the sample is exactly as the main results. Columns (1) and (4) only include a county and state-year FE, while the rest are based on the quasi-experimental research design that matches counties by risk, income, and population.

Results in columns (1) and (4) where I do not apply the quasi-experimental design clearly indicate that surprises are indeed correlated with losses as one might expect. This is to be expected since residents with lower priors are likely to engage less in private mitigation. This suggests that population or house price estimates based on this specification will confound the information impact of hurricanes.

Results in (2)-(3) and (5)-(6) where I use the quasi-experimental design clearly show that surprise does not predict hurricane losses, particularly in the case of counties with no history of hurricanes. Once counties are matched by risk, income, and population the expected level of damage is similar within the peer group. Within the group, variations in surprise *relative* *to the group average* are only based on residents' beliefs and do not predict expected damage.

Overall, this robustness shows that it is critical to control for differences in the underlying county characteristics when identifying the effect of surprise. Failing to do so will likely overestimate the information channel of hurricanes.

**Building Code Enforcement**: I have argued above that increases in house price growth paired with decrease in population growth suggest that the supply of housing may be reduced by stronger enforcement of local building standards. To test this I use data from the annual Census of Governments Finance and focus on the locally-financed spending on "Protective inspection and regulation". This is defined as: "regulation of private enterprise for the protection of the public and inspection of hazardous activities. This category includes expenditure on building code inspections and regulations". This category of spending generally includes salaries and capital outlays related to regulation activities by the county. While it is admittedly a noisy measure of building code enforcement, an increase in spending in the year after the hurricane is suggestive of higher regulation.

Results are listed in Table 10. Columns (1)-(2) use all of the reported data, which may not be reported by each county in every year and includes zeros. Columns (3)-(4) drop the zeros. All estimates for the effect of surprise are positive and the last two columns are statistically significant. They suggest that in the year after the hurricane, spending on enforcement of building codes increases more in counties with lower priors. As local governments internalize the "new news" from the hurricane and update their beliefs about weather risk, they increase spending on building code enforcement, leading to higher construction cost. This is consistent with the observed increase in house price growth.

**Alternative Surprise Measure Within Counties**: The within-county analysis of population and house prices focuses on the measure of pre-existing expectations based on flood insurance policies with above-minimum deductible. This measure compares communities where residents choose a higher deductible only when savings in insurance premiums are high (low-surprise) to those where residents select higher deductibles even when savings are lower (high-surprise). It will not identify expectations if all residents choose the minimum deductible. Furthermore, if the set of those with higher deductible is relatively small, the measure will not properly reflect the existing expectations. Here, I report and discuss results using the average of expectations of policy holders with minimum and above-minimum deductibles. The evidence is listed in Table 11. The estimated effects for population growth and growth of mail addresses closely match those in Table 7. Locations with lower pre-existing flood expectations experience bigger declines in growth rates. Similarly, in the case of real estate values, the results are consistent with those in the main section. Higher surprise is associated with smaller growth in house prices across towns within affected counties. Within towns, census tracts with higher direct impact experience slower growth in values.

**Population and House Prices: Post 2008 Sample**: The measure of surprise in the main results uses deductible choices to identify flood expectations. The data of flood insurance purchases lists active insurance policies starting 2008. To cover the entire sample from 2000, I use information on when insurance was first purchased. Flood insurance lapses can be costly for residents because they can lose their pre-existing status and flood insurance subsidy. This ensures that my measure will not consistently miss residents who had flood insurance but discontinued it. Yet, residents can change their deductible, particularly after hurricanes, and I may not be able to observe the original choice of deductible. If policy holders reduce deductibles after hurricanes and/or direct loss, my surprise measure will misidentify some high-surprise communities as low-surprise. As a result, the main results can underestimate the impact on population. In Table 12, I limit the sample to the post 2008 period, when I can precisely identify the deductible choice. As expected, the hurricanes surprises have a stronger negative effect on population and mailing-address growth. This is also the case with real estate values: house prices decline slightly more even in high-surprise locations.

**Out-migration to Other States and Flood Surprises**: In Table 5, I showed that hurricanes increase out-migration mainly in counties which experience their first hurricane during the sample (post 2000), while in-migration does not appear to be affected. Here, I examine how this changes based on the level of surprise in each county and further test whether out-migration is directed to the same state or residents tend to leave the state. The results are listed in Table 13. The evidence indicates that out-migration is higher in counties with a higher level of surprise, particularly using the average flood expectations of above-/minimum deductible choices. Interestingly, higher level of surprise has a very strong effect on migration to other states. This suggests hurricanes change flood expectations across a wider swath of areas within each state, i.e. those impacted by a near miss may have to leave the state in order to find a county with lower expected risk.

**Alternative Definition of Hurricane Impact**: How sensitive are the main results to the definition of hurricane impact being above 0.66%? I explore this by re-estimating the main specifications assuming that hurricane impact includes ares with over 0.33% in losses. Table B1, column (1) shows that counties with no hurricane history still experience a reduction in population growth but this is no longer significant. This suggests that less severe events are less likely to lead to expectations updating and more likely to be ignored as "flukes of nature". Within the group of counties with no previous hurricanes there is still evidence that those with lower prior are more likely to experience declines in population growth. This is evident in columns (3), (5), and (7). Turning to within-county evidence in Table B2, we see that the estimates are fairly consistent with the main results. Towns with lower priors are more likely to experience declines in population growth. House price data in Table B3 is also consistent with the main results. Overall, lowering the definition of hurricane severity appears to attenuate the results slightly but preserves the main conclusions.

**Alternative Definition of No Hurricane History**: How important is the recent hurricane experience for the main results? In this part I define hurricane history based on the experience up to 1995, instead of up to 2000.[28] This variation is expected to introduce counties with recent hurricane experience, between 1995 and 2000, in the group

[28] I also estimated the results up to 1999 and did not see any difference with the main results.

of no-previous-hurricane counties. In other words, for some of the counties of interest, the severe hurricane loss will not represent "new news" as they have already experienced a previous event and may have updated risk expectations. As expected, this attenuates the main results. Tables B4 through B6 show that the identified learning effect of disaster experience is weaker. The estimated interactions with Flood Expectation in Table B4 are negative but not all are statistically significant. The effect of surprise is also attenuated for population and house price growth within counties. Overall, the evidence further supports the interpretation that counties that experience a severe hurricane for a first time are more likely to update expectations. When they have experienced a hurricane previously updating is less empirically important

# 6 Conclusion

The evidence in this study suggests that direct damage and surprises, or information shocks, due to lower pre-existing flood expectations both have an effect *of similar magnitude* on growth after a hurricane. Most surprisingly, this is *not* consistent with a reduction in the demand for housing after adjustment in risk expectations, or at least suggests a relatively smaller reduction. Instead, the evidence points to a reduction in the supply of housing which is strong enough to lead to faster house-price growth even with slower population growth. This suggest that the slower population growth is a consequence of changes in expected risk that indirectly affect the location choice. Surprises can reshape the size of population and house prices as a result of measures taken by local communities as expected risk increases. This interpretation is at odds with the traditional view of self-selecting migration in the case of places with lower pre-hurricane expectations. Finally, I also find evidence that loss to sunk cost investment will lead to relocations since it reduces the cost of moving. This loss can be to residential buildings and to commercial facilities. The latter is consistent with findings that business loss and reduction in employment opportunities are likely to also drive migration. [29]

[29] There is a big literature on the economic impact of hurricanes on the local economy. See Petkov (2020).

# Statements and Declarations

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## Data Availability

The dataset generated and analyzed in the current study will be made available at request.

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# Tables and Figures

## Table 1: Summary Statistics for Counties with Hurricane Declarations 2000-2019

This table lists summary statistics at the county level for states with hurricanes. Hurricanes are based on major disaster declarations by FEMA between 2000 and 2019. The set of counties are divided into four groups: all counties (1-2), counties with hurricane-related disaster declaration (3-4), counties with damage over 0.66% (5-6), and counties with damage over 0.66% and no hurricanes during 1950-2000 (7-8). Demographic data comes from the annual Census estimates and IRS. Housing characteristics are based on FEMA data of flood insurance policies. Low-Damage Flood Surprise data uses the choice of deductible to infer the upper/lower bound of expected risk of flooding. The upper bound is calculated by comparing the current deductible choice with the lowest-possible one; the lower bound compares the current with a higher deductible choice; the average takes the mean of the upper/lower bounds. The reported surprise variables are the inverse of the expected probability of flooding. The adjusted surprise variables are the residuals from regressing individual expected probability on a set of insurance policy observables. N stands for the number of observations in the sample. Since data availability varies, I report the lowest number of observations.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *All Counties* | | *With Hurricane Declarations* | | *Damage ≥ .66%* | | *Damage ≥ .66% & No Pre'00 Hurricane* | |
| VARIABLES | mean | sd | mean | sd | mean | sd | mean | sd |
| *Demographic* | | | | | | | | |
| Population (1,000) | 98.54 | 316.0 | 134.1 | 301.7 | 161.6 | 471.9 | 153.7 | 460.7 |
| Housing Units (1,000) | 41.61 | 122.6 | 57.12 | 122.3 | 69.48 | 186.6 | 65.38 | 184.3 |
| Population Growth (%) | 0.279 | 1.465 | 0.545 | 1.492 | 0.257 | 1.580 | 0.0139 | 1.323 |
| Out-migration (1,000) | 4.436 | 12.11 | 6.671 | 14.61 | 8.090 | 20.63 | 7.956 | 22.20 |
| Out-migration Same State (1,000) | 2.530 | 6.968 | 3.867 | 8.821 | 4.760 | 12.40 | 4.602 | 12.36 |
| Out-migration Other State (1,000) | 1.914 | 5.703 | 2.861 | 6.378 | 3.330 | 8.571 | 3.355 | 9.937 |
| In-migration (1,000) | 4.442 | 11.16 | 6.941 | 14.33 | 8.188 | 18.61 | 6.780 | 16.90 |
| In-migration Same State (1,000) | 2.533 | 6.269 | 3.849 | 7.798 | 4.568 | 10.31 | 3.864 | 9.573 |
| In-migration Other State (1,000) | 1.916 | 5.680 | 3.129 | 7.074 | 3.620 | 8.780 | 2.915 | 7.653 |
| *Housing Characteristics* | | | | | | | | |
| Fraction in High-Risk Flood Zone (%) | 0.553 | 1.750 | 1.327 | 3.243 | 3.086 | 5.470 | 1.732 | 3.407 |
| Fraction in Direct-Impact Flood Zone (%) | 0.0142 | 0.141 | 0.0652 | 0.324 | 0.132 | 0.401 | 0.0237 | 0.0771 |
| Fraction in Low-Risk Flood Zone (%) | 0.317 | 1.068 | 0.775 | 1.872 | 1.747 | 2.797 | 1.177 | 1.916 |
| Fraction Pre-FIRM (%) | 0.468 | 1.056 | 0.873 | 1.681 | 1.814 | 2.505 | 1.355 | 1.874 |
| Fraction Elevated (%) | 0.233 | 1.083 | 0.764 | 2.315 | 1.866 | 3.990 | 0.674 | 1.249 |
| Fraction 3-Floor+ (%) | 0.152 | 0.788 | 0.462 | 1.610 | 0.979 | 2.414 | 0.383 | 1.239 |
| Fraction Town Houses (%) | 0.00116 | 0.0177 | 0.00473 | 0.0452 | 0.00918 | 0.0792 | 0.00320 | 0.0136 |
| Fraction High Community Risk Rating (%) | 0.118 | 1.121 | 0.479 | 2.209 | 1.259 | 3.822 | 0.770 | 2.939 |
| Fraction Non-Primary Residences (%) | 0.332 | 1.249 | 0.888 | 2.495 | 2.064 | 4.097 | 0.976 | 2.054 |
| Building Coverage (in \$100,000, 0=\$150,000) | -0.0707 | 0.725 | 0.105 | 0.741 | 0.264 | 0.922 | 0.129 | 1.187 |
| *Low-Damage Flood Suprise* | | | | | | | | |
| Flood Surprise Upper Bound (%) | -7.813 | 4.220 | -8.088 | 3.967 | -8.624 | 3.832 | -8.249 | 3.430 |
| Flood Surprise Upper Bound Adjusted (%) | 1.396 | 3.380 | 1.197 | 3.136 | 1.002 | 2.551 | 1.213 | 2.456 |
| Flood Surprise Average (%) | -6.440 | 3.628 | -6.503 | 3.418 | -7.022 | 3.409 | -7.027 | 3.106 |
| Flood Surprise Average Adjusted (%) | 0.659 | 2.775 | 0.476 | 2.617 | 0.455 | 2.044 | 0.358 | 2.230 |
| *Misc.* | | | | | | | | |
| County Hurricate Declaration | 0.0504 | 0.254 | 1 | 0 | 1 | 0 | 1 | 0 |
| Relative Hurricane Loss (%) | 0.0352 | 0.688 | 0.582 | 2.530 | 4.112 | 6.071 | 4.399 | 6.389 |
| Hurricane Loss ≥.66% | 0.00719 | 0.0845 | 0.125 | 0.331 | 1 | 0 | 1 | 0 |
| Predicted Risk of Loss ≥.66% | 12.00 | 6.124 | 16.46 | 9.979 | 22.76 | 15.11 | 14.10 | 8.049 |
| No Hurricane Declaration 1950-2000 | 0.839 | 0.368 | 0.449 | 0.498 | 0.334 | 0.473 | 1 | 0 |
| One+ Hurricane Declaration 1950-2000 | 0.160 | 0.367 | 0.551 | 0.498 | 0.666 | 0.473 | 0 | 0 |
| Per Capita Income (\$1,000) | 33.19 | 11.27 | 32.88 | 11.24 | 33.62 | 12.11 | 33.33 | 13.62 |
| House Price Index (FHFA) | 250.2 | 163.8 | 248.2 | 153.4 | 249.2 | 156.7 | 241.9 | 167.5 |
| Growth House Price Index (%) | 2.653 | 5.675 | 2.913 | 5.786 | 3.290 | 6.159 | 2.707 | 5.996 |
| N | 43,864 | | 1,852 | | 276 | | 95 | |

## Table 2: Determinants of Low-Damage Flood Expectations

This table reports coefficients estimates from regressing each of the measure of expected loss (at the policy or the county-average) on a set of characteristics listed in the insurance policy data. Estimates are based on different measures of expected probability of low-damage flood: columns (1)-(2) use the upper bound based on the residents who chose an above-minimum deductible; columns (3)-(4) average the expected probability of residents with above-minimum deductible (upper bound) and those who took the minimum deductible (lower bound);

| | (1) | (3) | (2) | (4) |
|---|---|---|---|---|
| Expectations Based on Insurance Deductibles: | *Above-Minimum* | | *Above- and Minimum* | |
| VARIABLES | *Individual* | *County Average* | *Individual* | *County Average* |
| Post-FIRM Construction | -0.0867*** | -0.0510*** | -0.0709*** | -0.0521*** |
| | (0.000233) | (0.00241) | (0.000115) | (0.00197) |
| Total Building Damage Coverage | 0.00230*** | 0.0259*** | 0.00238*** | 0.0236*** |
| | (1.74e-05) | (0.000896) | (1.37e-05) | (0.000760) |
| Total Contents Damage Coverage | 0.0386*** | 0.0230*** | 0.0228*** | 0.0168*** |
| | (0.000214) | (0.00250) | (0.000133) | (0.00211) |
| Low-Risk Flood Zone | -0.0299*** | -0.0211*** | -0.0222*** | -0.0243*** |
| | (0.000470) | (0.00296) | (0.000232) | (0.00229) |
| Direct-Impact High-Risk Flood Zone | 0.121*** | 0.173*** | 0.130*** | 0.125*** |
| | (0.000707) | (0.0175) | (0.000460) | (0.0151) |
| Elevated | -0.00587*** | 0.000202 | -0.00522*** | -0.00612*** |
| | (0.000271) | (0.00228) | (0.000141) | (0.00187) |
| Flood-Prevention Community Discount over 15% | 0.00754*** | 0.00309 | 0.000401*** | -0.00338 |
| | (0.000225) | (0.00347) | (0.000115) | (0.00298) |
| 3+ Floors | 0.0102*** | 0.0160*** | 0.0121*** | 0.0113*** |
| | (0.000356) | (0.00347) | (0.000215) | (0.00285) |
| Split-level | 0.0175*** | 0.0223** | 0.0161*** | 0.0211*** |
| | (0.00111) | (0.00876) | (0.000676) | (0.00749) |
| Manufactured Home | -0.0247*** | 0.0136** | -0.0143*** | 0.00325 |
| | (0.000809) | (0.00570) | (0.000407) | (0.00421) |
| Townhouse | 0.0757*** | 0.578 | 0.0535*** | -0.0989 |
| | (0.0142) | (1.071) | (0.00995) | (0.923) |
| Non-Primary Residence | 0.00583*** | -0.00396* | 0.00951*** | 0.000213 |
| | (0.000230) | (0.00208) | (0.000133) | (0.00171) |
| Observations | 370,700 | 2,640 | 875,908 | 2,723 |
| R-squared | 0.367 | 0.403 | 0.377 | 0.431 |

## Table 3: Distribution of Flood Surprise (Upper Bound): Counties with Damage ≥ .66%

This table provides a detailed view of the distribution of the rate of flood surprise (inverse of the expectation of flood risk) by each state in the sample. The left panel includes county observations for those with some pre-sample hurricanes. The right panel includes observations for those with no pre-sample hurricane.

| | One+ Hurricane Declaration 1950-2000 | | | | | No Hurricane Declaration 1950-2000 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| State | N | p25 | mean | p75 | sd | N | p25 | mean | p75 | sd |
| AL | 9 | -8.173 | -6.680 | -4.324 | 2.819 | 5 | -8.384 | -7.100 | -5.976 | 1.802 |
| FL | 66 | -10.30 | -8.225 | -5.840 | 3.349 | 24 | -10.21 | -9.074 | -8.137 | 2.581 |
| GA | 2 | -10.65 | -9.451 | -8.249 | 1.699 | 18 | -12.36 | -10.21 | -8.358 | 4.002 |
| LA | 45 | -6.697 | -5.912 | -4.554 | 1.575 | 7 | -7.022 | -5.690 | -4.528 | 1.630 |
| MD | 4 | -10.83 | -9.130 | -7.434 | 2.309 | 1 | -7.976 | -7.976 | -7.976 | |
| MS | 11 | -5.753 | -5.063 | -3.927 | 2.049 | 13 | -6.356 | -6.813 | -4.455 | 4.777 |
| NC | 54 | -9.528 | -8.202 | -6.191 | 2.659 | 3 | -9.670 | -7.629 | -6.247 | 1.804 |
| NJ | 5 | -10.35 | -10.47 | -10.18 | 0.679 | 2 | -14.84 | -12.03 | -9.220 | 3.975 |
| NY | 6 | -10.92 | -8.319 | -6.568 | 2.305 | 6 | -11.71 | -10.35 | -5.611 | 5.625 |
| PA | 1 | -7.732 | -7.732 | -7.732 | | 2 | -6.902 | -6.428 | -5.954 | 0.670 |
| TX | 26 | -10.08 | -8.668 | -7.591 | 2.344 | 32 | -8.482 | -7.426 | -6.267 | 1.942 |

# Table 4: Summary Statistics for Locations within Counties with Hurricane Damage $\geq$.66%

This table lists summary statistics for locations – state-place or census tract – within counties with 0.66% damage, depending on their pre-sample hurricane incidence. For information about variable definitions please refer to Table 1.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | **State Place Data** | | | | **Census Tract Data** | | | |
| | | | *No Pre'00 Hurricane* | | | | *No Pre'00 Hurricane* | |
| VARIABLES | mean | sd | mean | sd | mean | sd | mean | sd |
| *Demographic* | | | | | | | | |
| Population/Mailing Addresses (1,000) | 47.86 | 191.8 | 61.61 | 256.1 | 2.324 | 1.256 | 2.002 | 1.104 |
| Growth Population/Mailing Addresses (%) | 0.324 | 2.004 | -0.0291 | 1.523 | 0.651 | 8.825 | -0.214 | 14.71 |
| *Housing Characteristics* | | | | | | | | |
| Fraction in High-Risk Flood Zone (%) | 0.561 | 1.356 | 0.531 | 1.255 | 0.115 | 0.635 | 0.0795 | 0.263 |
| Fraction in Direct-Impact Flood Zone (%) | 0.0224 | 0.133 | 0.00722 | 0.0306 | 0.00510 | 0.0545 | 0.00117 | 0.0108 |
| Fraction in Low-Risk Flood Zone (%) | 0.414 | 0.862 | 0.415 | 0.801 | 0.0683 | 0.216 | 0.0527 | 0.146 |
| Fraction Pre-FIRM (%) | 0.338 | 0.596 | 0.424 | 0.746 | 0.0611 | 0.283 | 0.0546 | 0.147 |
| Fraction Elevated (%) | 0.298 | 0.847 | 0.195 | 0.486 | 0.0688 | 0.518 | 0.0251 | 0.102 |
| Fraction 3-Floor+ (%) | 0.205 | 0.680 | 0.122 | 0.414 | 0.0355 | 0.183 | 0.0137 | 0.0656 |
| Fraction Town Houses (%) | 0.00260 | 0.0358 | 0.00112 | 0.00655 | 0.000363 | 0.00576 | 0.000188 | 0.00336 |
| Fraction High Community Risk Rating (%) | 0.295 | 1.150 | 0.252 | 1.073 | 0.0474 | 0.259 | 0.0488 | 0.235 |
| Fraction Non-Primary Residences (%) | 0.398 | 1.074 | 0.292 | 0.686 | 0.0759 | 0.388 | 0.0405 | 0.145 |
| *Low-Damage Flood Surprise* | | | | | | | | |
| Flood Surprise Upper Bound (%) | -8.931 | 5.642 | -9.162 | 8.200 | -7.988 | 5.169 | -7.526 | 4.745 |
| Flood Surprise Upper Bound Adjusted (%) | 0.828 | 5.182 | 1.582 | 7.469 | 0.894 | 4.243 | 1.353 | 4.228 |
| Flood Surprise Average (%) | -7.230 | 5.299 | -8.176 | 8.151 | -6.468 | 4.570 | -6.492 | 4.426 |
| Flood Surprise Average Adjusted (%) | 0.418 | 3.856 | 0.705 | 5.789 | 0.491 | 3.596 | 0.949 | 3.766 |
| *Misc.* | | | | | | | | |
| County Hurricane Declaration | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| Hurricane Loss $\geq$.66% | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| No Hurricane Declaration 1950-2000 | 0.249 | 0.433 | 1 | 0 | 0.248 | 0.432 | 1 | 0 |
| Fraction Claimed Insurance (%) | 42.93 | 42.53 | 36.87 | 41.22 | 49.68 | 46.09 | 51.25 | 47.25 |
| ZHVI (in $100K centered at $150) / House Price Index (FHFA) | 0.967 | 2.370 | 0.941 | 3.325 | 219.7 | 92.75 | 227.4 | 108.6 |
| Growth ZHVI/House Price Index (%) | 3.727 | 6.342 | 3.596 | 4.340 | 3.930 | 10.36 | 2.844 | 8.886 |
| N | 812 | | 217 | | 3,855 | | 900 | |

# Table 5: The Effect of Hurricane Damage and Historical Hurricane Incidence on Population

This table provides estimates from two specifications: i) $\triangle \ln \text{Pop}_{c,t} = \beta \text{Hur}_{c,t-1} + \alpha_c + \psi_{PeerGroup(c),t} + \epsilon_{c,t}$; ii) $\triangle \ln \text{Pop}_{c,t} = \beta_1 \text{Hur}_{c,t-1} \text{NoHist}_c + \beta_2 \text{Hur}_{c,t-1} \text{YesHist}_c + \alpha_c + \psi_{PeerGroup(c),t} + \epsilon_{c,t}$. The outcome variable for the first eight estimates is population growth; the last four results focus on the log of out-/in-migration. Hurricanes are based on major disaster declarations by FEMA between 2000 and 2019. The sample consists of county-year observations for the year prior and during a hurricane disaster declaration. Hurricane is and indicator for counties with 0.66%+ damage. No Hurricane History/Yes Hurricane History is and indicator for zero/some hurricane declarations before the start of the sample: between 1950 and 2000. Columns (1) through (6) use an alternative specification for the peer/control group for affected counties. Column (1) uses a state-year fixed effect and assumes that all of the counties with presidential disaster declaration but below 0.66% damage serve as a control. Column (2) compares population responses only across counties with similar expected risk of higher damage – I introduce a RiskGr category which assigns each county with a hurricane declaration to a risk category. I assign categories by estimating a probit model of the ex-post damage above 0.66% on a set of housing characteristics and historical hurricane occurrence. Columns (3) and (4) interact the county's risk category with a population-size (PopGrp) or income-per-capita (IncGrp) category. Population size has three categories relative to cutoffs at 10,000 and 100,000 people. Income-per-capita category is based on cutoffs at \$20,000 and \$40,000. In column (6), I replace the risk category with a simple grouping based on the relative number of structures in the high-risk flood zone and an indicator for no history of hurricanes (FloodZoneGrp). The flood-zone group is based on the decile of the whole distribution of the variable in the sample.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | | | | *Growth Population* | | | | | *Log Out-Migration* | | *Log In-Migration* | |
| Hurricane | -0.00176** | -0.00191** | -0.00231*** | -0.00201** | -0.00223*** | -0.00250*** | | | | | | |
| | (0.000653) | (0.000742) | (0.000777) | (0.000788) | (0.000740) | (0.000869) | | | | | | |
| Hurricane x No Hurricane History | | | | | | | -0.00391** | -0.00197 | 0.0374** | 0.0327** | 0.0103 | 0.0223 |
| | | | | | | | (0.00170) | (0.00184) | (0.0159) | (0.0139) | (0.0172) | (0.0184) |
| Hurricane x Yes Hurricane History | | | | | | | -0.00155** | -0.00276*** | 0.000797 | 0.0110 | -0.0110 | -0.0193* |
| | | | | | | | (0.000737) | (0.000927) | (0.00870) | (0.00835) | (0.00888) | (0.0114) |
| Observations | 4,272 | 4,001 | 3,658 | 3,780 | 3,365 | 3,098 | 3,365 | 3,098 | 2,967 | 2,787 | 2,977 | 2,793 |
| R-squared | 0.822 | 0.841 | 0.854 | 0.852 | 0.866 | 0.869 | 0.866 | 0.869 | 0.999 | 0.999 | 0.999 | 0.999 |
| County FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State x Year FE | Yes | | | | | | | | | | | |
| State x RiskGrp x Year FE | | Yes | | | | | | | | | | |
| State x RiskGrp x PopGrp x Year FE | | | Yes | | | | | | | | | |
| State x RiskGrp x IncGrp x Year FE | | | | Yes | | | | | | | | |
| State x RiskGrp x PopGrp x IncGrp x Year FE | | | | | Yes | | Yes | | Yes | | Yes | |
| State x FloodZoneGrp x PopGrp x IncGrp x Year FE | | | | | | Yes | | Yes | | Yes | | Yes |

# Table 6: Flood Expectations in Counties with No Previous Hurricanes

This table provides estimates from specification (3). The outcome variable in each case is population growth. The sample consists of county-year observations for the year prior and during a hurricane disaster declaration, between 2000 and 2019 . Hurricane is and indicator for counties with 0.66%+ damage. No Hurricane History/Yes Hurricane History is and indicator for zero/some hurricane declarations before the start of the sample: between 1950 and 2000. Flood Surprise is the negative of the county average of expected probability of low-damage flood, inferred from the individual choice of deductible in the flood insurance policies of residents. Estimates are based on different measures of expected probability of low-damage flood: columns (2)-(3) use the upper bound based on the residents who chose an above-minimum deductible; columns (4)-(5) average the expected probability of residents with above-minimum deductible (upper bound) and those who took the minimum deductible (lower bound); columns (6)-(7) use the residuals after regressing the upper bound on housing characteristics; columns (8)-(9) use the residuals based on the upper and the lower bound. In each case, I estimate but do not report regressors specified in model (3). For details on the county peer groups, please see Table 5. The bottom panel reports the estimate of total impact of Hurricane in counties with no hurricane history for low levels of surprise (at the 25th percentile of the variable) and for high surprise (at the 75th percentile).

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | *Growth Population* | | | | | | | | |
| Expectations Based on Insurance Deductibles: | | *Above-Minimum* | | *Above- and Minimum* | | *Above-Minimum Adj* | | *Above- and Minimum Adj* | |
| Hurricane x No Hurricane History | -0.00391** | -0.00990*** | -0.0119*** | -0.00991*** | -0.0126*** | -0.00415** | -0.00212 | -0.00433*** | -0.00317* |
| | (0.00170) | (0.00269) | (0.00410) | (0.00251) | (0.00352) | (0.00165) | (0.00201) | (0.00165) | (0.00190) |
| Hurricane x No Hurricane History x Flood Surprise | | -0.0545** | -0.0966** | -0.0712*** | -0.131*** | -0.0992** | -0.180*** | -0.149** | -0.232*** |
| | | (0.0270) | (0.0430) | (0.0274) | (0.0377) | (0.0437) | (0.0664) | (0.0582) | (0.0574) |
| Observations | 3,365 | 2,624 | 2,367 | 2,776 | 2,517 | 2,624 | 2,367 | 2,776 | 2,517 |
| R-squared | 0.866 | 0.897 | 0.906 | 0.885 | 0.894 | 0.897 | 0.906 | 0.885 | 0.894 |
| County FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State-RiskGrp-PopIncGrp-Year FE | Yes | Yes | | Yes | | Yes | | Yes | |
| State-FloodZoneGrp-PopIncGrp-Year FE | | | Yes | | Yes | | Yes | | Yes |
| Low Surprise (25 percentile) | - | -0.00464*** | -0.00270 | -0.00437*** | -0.00253 | -0.00388** | -0.00173 | -0.00366** | -0.00204 |
| | | (0.00161) | (0.00198) | (0.00157) | (0.00180) | (0.00169) | (0.00204) | (0.00180) | (0.00188) |
| High Surprise (75 percentile) | - | -0.00666*** | -0.00581*** | -0.00630*** | -0.00559*** | -0.00709*** | -0.00671*** | -0.00712*** | -0.00671*** |
| | | (0.00167) | (0.00214) | (0.00167) | (0.00206) | (0.00176) | (0.00234) | (0.00142) | (0.00220) |

Table 7: Population Growth and Flood Surprises within Counties with No Hurricane History

This table provides estimates of model (4). Columns (1)-(4) are based on observations of population growth at towns (state-places) within counties which experience their first hurricane within the sample period. The sample drops towns with less than 3,000 residents. Columns (5)-(8) are based on observations of growth in mailing addresses in census tracts within towns that experience their first hurricane. The sample for these estimates starts in 2006 coinciding with the availability of the mailing addresses data. It drops census tracts with less than 300 residents. Impact is the fraction of of flood insurance claims (out of total active insurance policies) in the town/census tract. Surprise is the negative of the expected probability of low-damage flood, inferred from residents choosing above-minimum flood insurance deductible. Expected probability is calculated for each resident and is aggregated at the town/census tract level. High Impact is an indicator for top-quartile of fraction of insurance claims. High Surprise is an indicator for top-quartile of values of flood surprise. Estimates for the rest of the regressors specified in model (4) are omitted from the table. The bottom panel provides estimates for the effect of hurricane exposure at different levels of surprise.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | *Growth Population* | | | | *Growth Mailing Addresses* | | | |
| Impact | -0.0129** | -0.0113** | | | -0.00836 | 0.0228** | | |
| | (0.00617) | (0.00570) | | | (0.00540) | (0.0112) | | |
| Surprise | -0.0155*** | -0.0341*** | | | -0.0870** | -0.146*** | | |
| | (0.00401) | (0.00950) | | | (0.0377) | (0.0394) | | |
| Surprise x Impact | | 0.0265** | | | | 0.330*** | | |
| | | (0.0129) | | | | (0.127) | | |
| High Impact | | | -0.00816* | -0.0106* | | | 0.00389 | 0.00309 |
| | | | (0.00450) | (0.00552) | | | (0.00418) | (0.00456) |
| High Surprise | | | -0.00232** | -0.00343*** | | | -0.00485*** | -0.00559*** |
| | | | (0.00110) | (0.00128) | | | (0.00137) | (0.00118) |
| High Surprise x High Impact | | | | 0.0109* | | | | 0.00774** |
| | | | | (0.00557) | | | | (0.00372) |
| Observations | 7,533 | 7,533 | 7,533 | 7,533 | 6,990 | 6,990 | 6,990 | 6,990 |
| R-squared | 0.875 | 0.875 | 0.875 | 0.875 | 0.678 | 0.678 | 0.584 | 0.584 |
| State-Place FE | Yes | Yes | Yes | Yes | | | | |
| County-Year FE | Yes | Yes | Yes | Yes | | | | |
| Census Tract FE | | | | | Yes | Yes | Yes | Yes |
| State-Place-Year-FE | | | | | Yes | Yes | Yes | Yes |
| Additional Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Low Surprise x Low Impact | 0.00166*** | 0.00374*** | | | 0.00932** | 0.0156*** | | |
| | (0.000436) | (0.00104) | | | (0.00404) | (0.00422) | | |
| High Surprise x Low Impact | 0.000750*** | 0.00175*** | -0.00232** | -0.00343*** | 0.00253** | 0.00423*** | -0.00485*** | -0.00559*** |
| | (0.000204) | (0.000482) | (0.00110) | (0.00128) | (0.00109) | (0.00114) | (0.00137) | (0.00118) |
| Low Surprise x High Impact | | -0.00173 | | -0.0106* | | 0.0150*** | | 0.00309 |
| | | (0.00181) | | (0.00552) | | (0.00416) | | (0.00456) |
| High Surprise x High Impact | | -0.00313 | | -0.00310*** | | 0.00485*** | | 0.00524* |
| | | (0.00200) | | (0.00119) | | (0.00128) | | (0.00271) |

## Table 8: House Prices and Flood Surprises in Counties with No Hurricane History

This table provides estimates from specification (5). The outcome variable in each case is an annual measure of housing prices. The sample in columns (1)-(4) is based on Zillow's House Value Index aggregated at state-places; the sample in columns (5)-(8) is based on the FHFA's House Price Index aggregated at census tracts. In each case the sample includes annual observations for the period of 2000 to 2019. As in Table 7 the state-place sample drops towns with less than 3,000 residents and the census-tract sample drops tracts with less than 300 residents. Impact is the fraction of of flood insurance claims (out of total active insurance policies) in the town/census tract. Surprise is the negative of the expected probability of low-damage flood, inferred from residents choosing above-minimum flood insurance deductible. Expected probability is calculated for each resident and is aggregated at the town/census tract level. High Impact is an indicator for top-quartile of fraction of insurance claims. High Surprise is an indicator for top-quartile of values of flood surprise. Estimates for the rest of the regressors specified in model (4) are omitted from the table. The bottom panel provides estimates for the effect of hurricane exposure at different levels of surprise.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | *Growth Zillow House Value Index* | | | | *Growth FHFA House Price Index* | | | |
| Impact | 0.0132 | 0.0158* | | | -0.0411* | -0.0988** | | |
| | (0.00949) | (0.00890) | | | (0.0231) | (0.0439) | | |
| Surprise | 0.0478*** | 0.0104 | | | 0.0636 | 0.127 | | |
| | (0.0128) | (0.0160) | | | (0.122) | (0.136) | | |
| Surprise x Impact | | 0.0484*** | | | | -0.592* | | |
| | | (0.0183) | | | | (0.351) | | |
| High Impact | | | 0.0122* | 0.0144 | | | -0.0305*** | -0.0371*** |
| | | | (0.00739) | (0.00930) | | | (0.00495) | (0.00620) |
| High Surprise | | | 0.00587*** | 0.00643*** | | | -0.00656 | -0.0121*** |
| | | | (0.00222) | (0.00236) | | | (0.00481) | (0.00213) |
| High Surprise x High Impact | | | | -0.0103 | | | | 0.0292*** |
| | | | | (0.00879) | | | | (0.0107) |
| Observations | 3,609 | 3,609 | 3,609 | 3,609 | 10,504 | 10,504 | 10,502 | 10,502 |
| R-squared | 0.962 | 0.962 | 0.962 | 0.962 | 0.821 | 0.822 | 0.789 | 0.790 |
| State-Place FE | Yes | Yes | Yes | Yes | | | | |
| County-Year FE | Yes | Yes | Yes | Yes | | | | |
| Census Tract FE | | | | | Yes | Yes | Yes | Yes |
| State-Place-Year-FE | | | | | Yes | Yes | Yes | Yes |
| Additional Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Low Surprise x Low Impact | -0.00684*** | -0.00181 | | | -0.00705 | -0.0141 | | |
| | (0.00170) | (0.00218) | | | (0.0135) | (0.0151) | | |
| High Surprise x Low Impact | -0.00257*** | -0.000626 | 0.00587*** | 0.00643*** | -0.00184 | -0.00369 | -0.00656 | -0.0121*** |
| | (0.000627) | (0.000815) | (0.00222) | (0.00236) | (0.00352) | (0.00394) | (0.00481) | (0.00213) |
| Low Surprise x High Impact | | 0.00310 | | 0.0144 | | -0.0162 | | -0.0371*** |
| | | (0.00428) | | (0.00930) | | (0.0150) | | (0.00620) |
| High Surprise x High Impact | | 0.00643 | | 0.0105 | | -0.00887* | | -0.0199** |
| | | (0.00455) | | (0.00659) | | (0.00517) | | (0.00840) |

## Table 9: Hurricane Losses and Surprise: Quasi-Experimental Design

This table provides estimates from a variation of specification (3) where the outcome variable is the actual county loss during a hurricane impact (as a fraction of GDP). Flood Surprise is the negative of the county average of expected probability of low-damage flood, inferred from the individual choice of deductible in the flood insurance policies of residents. All columns use the Above-Minimum flood surprise measure. All estimates use the upper bound based on the residents who chose an above-minimum deductible. No Hurricane History/Yes Hurricane History is and indicator for zero/some hurricane declarations before the start of the sample: between 1950 and 2000. For details on the county peer groups, please see Table 5.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | | | *Hurricane Losses* | | | |
| Flood Surprise | 0.0801** | 0.0490 | 0.0408 | | | |
| | (0.0335) | (0.0323) | (0.0379) | | | |
| Flood Surprise x No Hurricane History | | | | 0.0757** | 0.00510 | 0.0124 |
| | | | | (0.0333) | (0.0402) | (0.0318) |
| Flood Surprise x Yes Hurricane History | | | | 0.0836** | 0.0687 | 0.0668 |
| | | | | (0.0346) | (0.0424) | (0.0663) |
| Observations | 3,477 | 2,624 | 2,367 | 3,477 | 2,624 | 2,367 |
| R-squared | 0.510 | 0.672 | 0.684 | 0.510 | 0.673 | 0.684 |
| County FE | Yes | Yes | Yes | Yes | Yes | Yes |
| State-Year FE | Yes | - | - | Yes | - | - |
| State-RiskGrp-PopIncGrp-Year FE | - | Yes | - | - | Yes | Yes |
| State-FloodZoneGrp-PopIncGrp-Year FE | - | - | Yes | - | - | - |

## Table 10: Surprises and Building Code Enforcement

This table provides estimates from a variation of specification (3) where the outcome variable is county spending on protective inspection and regulation (as a fraction of GDP). Columns (1)-(2) use the full sample of available county spending data. Columns (3)-(4) drop non-reported or zero values. Flood Surprise is the negative of the county average of expected probability of low-damage flood, inferred from the individual choice of deductible in the flood insurance policies of residents. All columns use the Above-Minimum flood surprise measure. All estimates use the upper bound based on the residents who chose an above-minimum deductible. No Hurricane History/Yes Hurricane History is and indicator for zero/some hurricane declarations before the start of the sample: between 1950 and 2000. For details on the county peer groups, please see Table 5.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | | *County Inspection Spending* | | |
| Hurricane x No History of Hurricanes | -2.96e-05 | 7.38e-05 | 0.000536 | 5.82e-05 |
| | (7.35e-05) | (8.76e-05) | (0.000348) | (0.000126) |
| Hurricane x No History of Hurricanes x Flood Expectation | 0.000482 | 0.00136 | 0.00753** | 0.00210* |
| | (0.000885) | (0.00113) | (0.00337) | (0.00114) |
| Observations | 1,135 | 1,008 | 561 | 470 |
| R-squared | 0.975 | 0.975 | 0.979 | 0.977 |
| County FE | Yes | Yes | Yes | Yes |
| State-RiskGrp-PopIncGrp-Year FE | Yes | | Yes | |
| State-FloodZoneGrp-PopIncGrp-Year FE | | Yes | | Yes |

## Table 11: Population and House Prices in Counties with No Hurricane History: Alternative Surprise Measure

This table provides estimates of model (4) and (5) using an alternative measure of surprise. Columns (1)-(4) follow the sample and variable definitions from Table 7. Columns (5)-(8) follow the sample and variable definitions from Table 8. In all cases Surprise is the inverse of the average of the implicit flood risk from both the minimum- and above-minimum deductible policies. For additional information please refer to Table 7 and Table 8.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *Growth Population* | | *Growth Mail Addresses* | | *Growth Zillow HVI* | | *Growth FHFA HPI* | |
| Impact | -0.0130** | -0.0115** | -0.00721 | 0.0160* | 0.0128 | 0.0164* | -0.0364** | -0.0594** |
| | (0.00611) | (0.00563) | (0.00485) | (0.00899) | (0.0101) | (0.00987) | (0.0147) | (0.0252) |
| Surprise | -0.0165*** | -0.0392*** | -0.0813* | -0.136*** | 0.0399** | -0.0197 | -0.0861 | -0.0284 |
| | (0.00412) | (0.0127) | (0.0433) | (0.0459) | (0.0164) | (0.0162) | (0.130) | (0.151) |
| Surprise x Impact | | 0.0307* | | 0.299** | | 0.0756*** | | -0.323 |
| | | (0.0158) | | (0.123) | | (0.0191) | | (0.277) |
| Observations | 8,457 | 8,457 | 8,429 | 8,429 | 4,080 | 4,080 | 13,416 | 13,416 |
| R-squared | 0.885 | 0.885 | 0.636 | 0.636 | 0.961 | 0.961 | 0.823 | 0.823 |
| State-Place FE | Yes | Yes | | | Yes | Yes | | |
| County-Year FE | Yes | Yes | | | Yes | Yes | | |
| Census Tr - FE | | | Yes | Yes | | | Yes | Yes |
| State-Place-Year-FE | | | Yes | Yes | | | Yes | Yes |
| Additional Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Low Surprise x Low Impact | 0.00151*** | 0.00363*** | 0.00712* | 0.0119*** | -0.00446** | 0.00199 | 0.00644 | 0.00212 |
| | (0.000378) | (0.00118) | (0.00379) | (0.00402) | (0.00174) | (0.00177) | (0.00969) | (0.0113) |
| High Surprise x Low Impact | 0.000704*** | 0.00171*** | 0.00240* | 0.00402*** | -0.00156*** | 0.000753 | 0.00248 | 0.000818 |
| | (0.000178) | (0.000558) | (0.00128) | (0.00136) | (0.000602) | (0.000621) | (0.00374) | (0.00436) |
| Low Surprise x High Impact | | -0.00154 | | 0.0113*** | | 0.00563 | | -0.000394 |
| | | (0.00165) | | (0.00393) | | (0.00411) | | (0.0112) |
| High Surprise x High Impact | | -0.00291 | | 0.00441*** | | 0.00673 | | -0.00276 |
| | | (0.00183) | | (0.00142) | | (0.00425) | | (0.00491) |

## Table 12: Population and House Prices in Counties with No Hurricane History: Post 2008

This table provides estimates of model (4) and (5) restricting the sample to observations post 2008. Columns (1)-(4) follow the sample and variable definitions from Table 7. Columns (5)-(8) follow the sample and variable definitions from Table 8. In all cases Surprise is the inverse of the average of the implicit flood risk from both the minimum- and above-minimum deductible policies. For additional information please refer to Table 7 and Table 8.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *Growth Population* | | *Growth Mail Addresses* | | *Growth Zillow HVI* | | *Growth FHFA HPI* | |
| Impact | -0.0263** | -0.0237** | -0.0118** | 0.0156 | 0.0204** | 0.0231*** | -0.0760*** | -0.113 |
| | (0.0126) | (0.0121) | (0.00481) | (0.0106) | (0.00841) | (0.00847) | (0.0289) | (0.0850) |
| Surprise | -0.0238** | -0.0589*** | -0.0878** | -0.136*** | 0.0576*** | 0.000922 | 0.233 | 0.311 |
| | (0.0116) | (0.0166) | (0.0411) | (0.0398) | (0.0143) | (0.0238) | (0.321) | (0.368) |
| Surprise x Impact | | 0.0446*** | | 0.276** | | 0.0745** | | -0.382 |
| | | (0.0153) | | (0.117) | | (0.0330) | | (0.754) |
| Observations | 4,232 | 4,232 | 6,416 | 6,416 | 2,272 | 2,272 | 6,136 | 6,136 |
| R-squared | 0.764 | 0.764 | 0.558 | 0.558 | 0.942 | 0.942 | 0.715 | 0.715 |
| State-Place FE | Yes | Yes | | | Yes | Yes | | |
| County-Year FE | Yes | Yes | | | Yes | Yes | | |
| Census Tr - FE | | | Yes | Yes | | | Yes | Yes |
| State-Place-Year-FE | | | Yes | Yes | | | Yes | Yes |
| Additional Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Low Surprise x Low Impact | 0.00239* | 0.00654*** | 0.00949** | 0.0148*** | -0.00848*** | -0.000174 | -0.0258 | -0.0344 |
| | (0.00129) | (0.00180) | (0.00444) | (0.00430) | (0.00210) | (0.00343) | (0.0356) | (0.0408) |
| High Surprise x Low Impact | 0.000954 | 0.00304*** | 0.00256** | 0.00398*** | -0.00324*** | 8.53e-05 | -0.00708 | -0.00944 |
| | (0.000606) | (0.000826) | (0.00120) | (0.00116) | (0.000826) | (0.00134) | (0.00975) | (0.0112) |
| Low Surprise x High Impact | | -0.0124* | | 0.0141*** | | 0.0121 | | -0.0395 |
| | | (0.00727) | | (0.00423) | | (0.00903) | | (0.0405) |
| High Surprise x High Impact | | -0.0141* | | 0.00432*** | | 0.0189** | | -0.0167 |
| | | (0.00766) | | (0.00122) | | (0.00862) | | (0.0136) |

## Table 13: Flood Expectations in Counties with No Previous Hurricanes: Out-migration to Other States

This table provides estimates from specification (2). The outcome variables are the log of total out-migration and out-migration only to a different state. Hurricanes are based on major disaster declarations by FEMA between 2000 and 2019. The sample consists of county-year observations for the year prior and during a hurricane disaster declaration. Hurricane is and indicator for counties with 0.66%+ damage. No Hurricane History is and indicator for zero hurricane declarations before the start of the sample: between 1950 and 2000. For more information please refer to Table 5.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *Log Out-Migration* | | | |
| | *All States* | *Other States* | *All States* | *Other States* |
| Expectations Based on Insurance Deductibles: | *Above-Minimum* | | *Above- and Minimum* | |
| Hurricane x No History of Hurricanes | 0.0700** | 0.138* | 0.0849*** | 0.136** |
| | (0.0343) | (0.0729) | (0.0295) | (0.0533) |
| Hurricane x No History of Hurricanes x Flood Surprise | 0.508 | 1.411** | 0.751** | 1.582*** |
| | (0.349) | (0.661) | (0.297) | (0.542) |
| Observations | 2,307 | 2,307 | 2,445 | 2,445 |
| R-squared | 0.999 | 0.998 | 0.999 | 0.998 |
| County FE | Yes | Yes | Yes | Yes |
| State-RiskGrp-PopIncGrp-Year FE | Yes | Yes | Yes | Yes |
| Low Surprise | 0.0223 | 0.00555 | 0.0256 | 0.0111 |
| | (0.0190) | (0.0294) | (0.0176) | (0.0302) |
| High Surprise | 0.0395* | 0.0533 | 0.0479** | 0.0582* |
| | (0.0202) | (0.0398) | (0.0198) | (0.0348) |

# Appendix (for online publication)

## Appendix A: Data Construction

### Hurricane Damage

The SBA dataset of verified residential and business damage is based on applications for low-interest loans to cover uninsured losses. It includes the total loan amount requested, loss incurred, and the location of the property. I use the publicly-available version, aggregated at the zip-code and city/county for each disaster. Since the non-public data includes all applications with the corresponding verified loss, the public data approximates the overall uninsured loss.

FEMA provides non-repayable grants to homeowners and renters to cover disaster losses through its Individuals and Households Program (IHP). Payments help with immediate needs following disasters and supplement other sources of recovery funds. I use information from IHP for homeowners, which includes total property damage, determined by FEMA inspectors.

The IHP data for renters and homeowners lists the amount of rental assistance provided for households which are displaced. Property damage measures uninsured residential loss and rental relief proxies for population displacement. FEMA provides state and local governments grants to help respond/recover after disasters through the Public Assistance (PA) program. The PA data includes damage to roads and bridges, water control facilities, public buildings, and public utilities. It also provides funds for the necessary removal of debris and protective measures. I use the total amount of public assistance paid to each county to approximate the amount of damage to the public infrastructure. I identify the insured loss caused by flooding with data on insurance claims from the National Flood Insurance Program (NFIP).[30] For each claim the data includes the census tract level, the amount paid, the date on which the loss was incurred, as well as the characteristics of the structure (including the flood zone). I match the date of loss to the hurricane date in each county to identify whether the insurance claim is related to a disaster declaration.

### Expected Flood Loss

I calculate the implicit upper bound of expected probability of low-damage flood by focusing only on insurance policies with above-minimum deductibles. Table B7 lists the possible choices for the years after (and including) 2010. For that period the lowest deductible was \$1,000/\$1,000 for building/contents loss. I start with policies with \$2,000/\$1,000 and calculate the change in the premium if they were to choose the \$1,000/\$1,000 option: from 0.95 to 1 or a 5% increase in the premium. Since I observe the current premium paid, I can calculate the amount by which the premium increases if the household chooses the lowest deductible. The formula for the implicit upper bound of expected loss is:

$$ExpProb_{upper} = \frac{\triangle Premium}{\triangle Deductible} \tag{6}$$

[30] This is publicly available on FEMA's website.

I continue with policies with \$2,000/\$2,000 and identify the change in the premium based on the factors from Table B7. Based on the increase in the premium and the reduction in the deductible, I can calculate the upper bound of the expected probability. Altogether, I match \$2,000/\$1,000, \$2,000/\$2,000, \$3,000/\$1,000, \$3,000/\$2,000, and , \$3,000/\$3,000 to the lowest option of \$1,000/\$1,000.

In the period before 2010, the lowest deductible option is \$500/\$500. In that case I match \$1,000/\$500, \$2,000/\$500, \$1,000/\$1,000, \$2,000/\$1,000, and \$2,000/\$2,000 to the lowest option of \$500/\$500.

To calculate the lower-bound of expected probability, I focus on policies with \$500/\$500 or \$1,000/\$1,000, depending on the period. I then identify the change in the premium factor if the household chooses \$1,000/\$500 or \$2,000/\$1,000, respectively. I the formula in (6) based on the change in the premium and deductible.

## Appendix B: Robustness

# Table B1: Alternative Impact Definition: Flood Expectations in Counties with No Previous Hurricanes

This table provides estimates from specification (3). The outcome variable in each case is population growth. The sample consists of county-year observations for the year prior and during a hurricane disaster declaration, between 2000 and 2019 . Hurricane is and indicator for counties with 0.33%+ damage. No Hurricane History/Yes Hurricane History is and indicator for zero/some hurricane declarations before the start of the sample: between 1950 and 2000. Flood Surprise is the negative of the county average of expected probability of low-damage flood, inferred from the individual choice of deductible in the flood insurance policies of residents. Estimates are based on different measures of expected probability of low-damage flood: columns (2)-(3) use the upper bound based on the residents who chose an above-minimum deductible; columns (4)-(5) average the expected probability of residents with above-minimum deductible (upper bound) and those who took the minimum deductible (lower bound); columns (6)-(7) use the residuals after regressing the upper bound on housing characteristics; columns (8)-(9) use the residuals based on the upper and the lower bound. In each case, I estimate but do not report regressors specified in model (3). For details on the county peer groups, please see Table 5. The bottom panel reports the estimate of total impact of Hurricane in counties with no hurricane history for low levels of surprise (at the 25th percentile of the variable) and for high surprise (at the 75th percentile).

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | *Growth Population* | | | | | | | | |
| Expectations Based on Insurance Deductibles: | | *Above-Minimum* | | *Above- and Minimum* | | *Above-Minimum Adj* | | *Above- and Minimum Adj* | |
| Hurricane x No History of Hurricanes | -0.000762 | -0.00197 | -0.00608** | -0.00241 | -0.00619** | -0.00227 | 1.84e-05 | -0.00184 | -0.000175 |
| | (0.00128) | (0.00269) | (0.00277) | (0.00245) | (0.00261) | (0.00163) | (0.00179) | (0.00143) | (0.00150) |
| Hurricane x No History of Hurricanes x Flood Expectation | | 0.00473 | -0.0631** | -0.00704 | -0.0830*** | -0.00461 | -0.0932* | -0.0180 | -0.122*** |
| | | (0.0329) | (0.0315) | (0.0345) | (0.0316) | (0.0437) | (0.0513) | (0.0437) | (0.0393) |
| Observations | 3,385 | 2,631 | 2,367 | 2,790 | 2,517 | 2,631 | 2,367 | 2,790 | 2,517 |
| R-squared | 0.868 | 0.896 | 0.905 | 0.884 | 0.893 | 0.896 | 0.905 | 0.884 | 0.893 |
| County FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State-RiskGrp-PopIncGrp-Year FE | Yes | Yes | | Yes | | Yes | | Yes | |
| State-FloodZoneGrp-PopIncGrp-Year FE | | | Yes | | Yes | | Yes | | Yes |

## Table B2: Alternative Impact Definition: Population Growth and Flood Surprises within Counties with No Hurricane History

This table provides estimates of model (4). Columns (1)-(4) are based on observations of population growth at towns (state-places) within counties which experience their first hurricane within the sample period. The sample drops towns with less than 3,000 residents. Impact is the fraction of of flood insurance claims (out of total active insurance policies) in the town. Surprise is the negative of the expected probability of low-damage flood, inferred from residents choosing above-minimum flood insurance deductible. Expected probability is calculated for each resident and is aggregated at the town. High Impact is an indicator for top-quartile of fraction of insurance claims. High Surprise is an indicator for top-quartile of values of flood surprise. Estimates for the rest of the regressors specified in model (4) are omitted from the table.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | | *Growth Population* | | |
| Impact | -0.00711* | -0.00486 | | |
| | (0.00412) | (0.00385) | | |
| Surprise | -0.0166*** | -0.0398*** | | |
| | (0.00439) | (0.0129) | | |
| Surprise x Impact | | 0.0341** | | |
| | | (0.0156) | | |
| High Impact | | | -0.00629 | -0.00834* |
| | | | (0.00445) | (0.00477) |
| High Surprise | | | -0.00154 | -0.00316** |
| | | | (0.00125) | (0.00134) |
| High Surprise x High Impact | | | | 0.00963** |
| | | | | (0.00410) |
| Observations | 7,533 | 7,533 | 7,533 | 7,533 |
| R-squared | 0.875 | 0.875 | 0.875 | 0.875 |
| State-Place FE | Yes | Yes | Yes | Yes |
| County-Year FE | Yes | Yes | Yes | Yes |
| Additional Controls | Yes | Yes | Yes | Yes |

# Table B3: Alternative Impact Definition: House Prices and Flood Surprises within Counties with No Hurricane History

This table provides estimates of model (4). Columns (1)-(4) are based on observations of population growth at towns (state-places) within counties which experience their first hurricane within the sample period. The sample drops towns with less than 3,000 residents. Impact is the fraction of of flood insurance claims (out of total active insurance policies) in the town. Surprise is the negative of the expected probability of low-damage flood, inferred from residents choosing above-minimum flood insurance deductible. Expected probability is calculated for each resident and is aggregated at the town. High Impact is an indicator for top-quartile of fraction of insurance claims. High Surprise is an indicator for top-quartile of values of flood surprise. Estimates for the rest of the regressors specified in model (4) are omitted from the table.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | *Growth Zillow House Value Index* | | | |
| Impact | 0.0126 | 0.0156* | | |
| | (0.00959) | (0.00868) | | |
| Surprise | 0.0558*** | 0.0186 | | |
| | (0.0122) | (0.0200) | | |
| Surprise x Impact | | 0.0486* | | |
| | | (0.0279) | | |
| High Impact | | | 0.0156*** | 0.0113 |
| | | | (0.00525) | (0.00762) |
| High Surprise | | | 0.0114** | 0.00828*** |
| | | | (0.00527) | (0.00262) |
| | | | (0.00125) | (0.00134) |
| High Surprise x High Impact | | | | 0.0250 |
| | | | | (0.0205) |
| Observations | 3,609 | 3,609 | 3,609 | 3,609 |
| R-squared | 0.962 | 0.962 | 0.962 | 0.962 |
| State-Place FE | Yes | Yes | Yes | Yes |
| County-Year FE | Yes | Yes | Yes | Yes |
| Additional Controls | Yes | Yes | Yes | Yes |

## Table B4: No Hurricanes History Pre 1995: Flood Expectations in Counties with No Previous Hurricanes

This table provides estimates from specification (3). The outcome variable in each case is population growth. The sample consists of county-year observations for the year prior and during a hurricane disaster declaration, between 2000 and 2019 . Hurricane is and indicator for counties with 0.66%+ damage. No Hurricane History/Yes Hurricane History is and indicator for zero/some hurricane declarations before the start of the sample: between 1950 and 1995. Flood Surprise is the negative of the county average of expected probability of low-damage flood, inferred from the individual choice of deductible in the flood insurance policies of residents. Estimates are based on different measures of expected probability of low-damage flood: columns (2)-(3) use the upper bound based on the residents who chose an above-minimum deductible; columns (4)-(5) average the expected probability of residents with above-minimum deductible (upper bound) and those who took the minimum deductible (lower bound); columns (6)-(7) use the residuals after regressing the upper bound on housing characteristics; columns (8)-(9) use the residuals based on the upper and the lower bound. In each case, I estimate but do not report regressors specified in model (3). For details on the county peer groups, please see Table 5. The bottom panel reports the estimate of total impact of Hurricane in counties with no hurricane history for low levels of surprise (at the 25th percentile of the variable) and for high surprise (at the 75th percentile).

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| VARIABLES | | | | | *Growth Population* | | | | |
| Expectations Based on Insurance Deductibles: | | *Above-Minimum* | | *Above- and Minimum* | | *Above-Minimum Adj* | | *Above- and Minimum Adj* | |
| Hurricane x No History of Hurricanes | -0.00275*** | -0.00664*** | -0.00361 | -0.00805*** | -0.00486* | -0.00315*** | -0.00308*** | -0.00322*** | -0.00259** |
| | (0.000996) | (0.00249) | (0.00288) | (0.00225) | (0.00280) | (0.000992) | (0.00102) | (0.000972) | (0.00103) |
| Hurricane x No History of Hurricanes x Flood Expectation | | -0.0367 | -0.00534 | -0.0670** | -0.0313 | -0.0424 | -0.0120 | -0.0614 | -0.0319 |
| | | (0.0258) | (0.0324) | (0.0276) | (0.0396) | (0.0481) | (0.0476) | (0.0631) | (0.0669) |
| Observations | 3,229 | 2,496 | 2,386 | 2,664 | 2,539 | 2,496 | 2,386 | 2,664 | 2,539 |
| R-squared | 0.870 | 0.902 | 0.910 | 0.891 | 0.898 | 0.902 | 0.910 | 0.891 | 0.897 |
| County FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| State-RiskGrp-PopIncGrp-Year FE | Yes | Yes | | Yes | | Yes | | Yes | |
| State-FloodZoneGrp-PopIncGrp-Year FE | | | Yes | | Yes | | Yes | | Yes |

# Table B5: No Hurricanes History Pre 1995: Population Growth and Flood Surprises within Counties with No Hurricane History

This table provides estimates of model (4). Columns (1)-(4) are based on observations of population growth at towns (state-places) within counties which experience their first hurricane within the sample period. The sample drops towns with less than 3,000 residents. Impact is the fraction of of flood insurance claims (out of total active insurance policies) in the town. Surprise is the negative of the expected probability of low-damage flood, inferred from residents choosing above-minimum flood insurance deductible. Expected probability is calculated for each resident and is aggregated at the town level. High Impact is an indicator for top-quartile of fraction of insurance claims. High Surprise is an indicator for top-quartile of values of flood surprise. Estimates for the rest of the regressors specified in model (4) are omitted from the table.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | | | *Growth Population* | |
| Impact | -0.00508** | -0.00345 | | |
| | (0.00254) | (0.00237) | | |
| Surprise | -0.0167*** | -0.0298*** | | |
| | (0.00332) | (0.00666) | | |
| Surprise x Impact | | 0.0216** | | |
| | | (0.00942) | | |
| High Impact | | | -0.00304 | -0.00359* |
| | | | (0.00190) | (0.00214) |
| High Surprise | | | -0.00107* | -0.00159** |
| | | | (0.000650) | (0.000691) |
| High Surprise x High Impact | | | | 0.00410* |
| | | | | (0.00235) |
| Observations | 7,533 | 7,533 | 7,533 | 7,533 |
| R-squared | 0.875 | 0.875 | 0.875 | 0.875 |
| State-Place FE | Yes | Yes | Yes | Yes |
| County-Year FE | Yes | Yes | Yes | Yes |
| Additional Controls | Yes | Yes | Yes | Yes |

## Table B6: No Hurricanes History Pre 1995: House Prices and Flood Surprises within Counties with No Hurricane History

This table provides estimates of model (4). Columns (1)-(4) are based on observations of population growth at towns (state-places) within counties which experience their first hurricane within the sample period. The sample drops towns with less than 3,000 residents. Impact is the fraction of of flood insurance claims (out of total active insurance policies) in the town. Surprise is the negative of the expected probability of low-damage flood, inferred from residents choosing above-minimum flood insurance deductible. Expected probability is calculated for each resident and is aggregated at the town level. High Impact is an indicator for top-quartile of fraction of insurance claims. High Surprise is an indicator for top-quartile of values of flood surprise. Estimates for the rest of the regressors specified in model (4) are omitted from the table.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | *Growth Zillow House Value Index* | | | |
| Impact | -0.00156 | 0.00170 | | |
| | (0.00603) | (0.00624) | | |
| Surprise | 0.0424*** | 0.0154 | | |
| | (0.0137) | (0.0210) | | |
| Surprise x Impact | | 0.0401* | | |
| | | (0.0235) | | |
| High Impact | | | -0.00299 | -0.00172 |
| | | | (0.00512) | (0.00527) |
| High Surprise | | | 0.00349 | 0.00444 |
| | | | (0.00415) | (0.00415) |
| High Surprise x High Impact | | | | -0.00985 |
| Observations | 3,609 | 3,609 | 3,609 | 3,609 |
| R-squared | 0.962 | 0.962 | 0.962 | 0.962 |
| State-Place FE | Yes | Yes | Yes | Yes |
| County-Year FE | Yes | Yes | Yes | Yes |
| Additional Controls | Yes | Yes | Yes | Yes |

## Table B7: Deductible Factors: Single Family Post 2010

This table lists deductible choices and the premium factors associated with each option. The characteristics of the insured house and the amount of coverage determine the baseline premium. The choice of deductible can scale up or down the final premium due.

| Deductible Options: Building/Contents | Post-FIRM $1,000 Ded. | Pre-FIRM $2,000 Ded. |
|---|---|---|
| $1,000/$1,000 | 1 | 1.1 |
| $2,000/$1,000 | 0.95 | 1.03 |
| $2,000/$2,000 | 0.925 | 1 |
| $3,000/$1,000 | 0.9 | 0.98 |
| $3,000/$2,000 | 0.875 | 0.95 |
| $3,000/$3,000 | 0.85 | 0.925 |
| $4,000/$1,000 | 0.85 | 0.9 |
| $4,000/$2,000 | 0.825 | 0.9 |
| $4,000/$3,000 | 0.8 | 0.875 |
| $4,000/$4,000 | 0.775 | 0.85 |
| $5,000/$1,000 | 0.825 | 0.9 |
| $5,000/$2,000 | 0.8 | 0.875 |
| $5,000/$3,000 | 0.78 | 0.85 |
| $5,000/$4,000 | 0.765 | 0.83 |
| $5,000/$5,000 | 0.75 | 0.81 |