Not For Publication

Online Appendix for
"Learning about an Infrequent Event:
Evidence from Flood Insurance Take-up in the US"

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A Insurance Model

The manuscript uses the straightforward prediction that insurance take-up will increase (decrease) if homeowners in a community revise upwards (downwards) their expectation of a future flood. This section of the Appendix uses a simple insurance model to provide more details on this prediction and to show how the economic model relates to the estimating equation.

Each year homeowners purchase the level of flood insurance that maximizes their expected utility given their belief about the probability of a flood.

$$max_{q_{ict}} E_t[u(q_{ict}, w_i, l_i, r_i, p_{ict})] = p_{ict} * u(w_i - l_i - r_i q_{ict} + q_{ict}) + (1 - p_{ict}) * u(w_i - r_i q_{ict}) \quad (1)$$

q_{ict} is the level of flood insurance selected by homeowner i in community c in year t. There are four parameters. The parameter of interest is p_{ict}, the homeowner belief of the yearly flood probability in time t. w_i is homeowner wealth and l_i is the amount of flood damage conditional on being hit by a flood. $r_i \in (0, 1)$ is the dollar rate per \$1 of flood insurance. Recall from Section 2 in the manuscript that the price of insurance is not experience rated, is set at "actuarial" rates (plus a uniform loading factor), and is (essentially) constant in real dollars. As such, r_i can be thought of as a fixed parameter set by NFIP actuaries that depends on the location of homeowner i's house.

Each homeowner chooses the level of insurance, q^*_{ict}, that maximizes expected utility at the end of the calendar year after observing whether there is a flood and updating beliefs p_{ict}. The homeowner flood insurance model has a straightforward prediction: If a homeowner's belief over future flooding increases, then the utility maximizing level of flood insurance will increase. The comparative static, $\frac{\partial q^*_{ict}}{\partial p_{ict}}$, is greater than zero by the implicit function theorem, provided $u' > 0$ and $u'' < 0$.[1]

The flood insurance data used in this paper are aggregated at the community level. I also consider a log linear approximation of the homeowner insurance decision that lends itself to the same event study framework as in Section 3 of the manuscript.

$$f_{ict}(0) = p_{ict}(1 - r_i) * u'(w_i - L_i) - r_i(1 - p_{ict}) * u'(w_i) \quad (2)$$

Equation (2) defines $f_{ict}(0)$ as an implicit function equal to the homeowner First Order Condition at $q_{ict} = 0$. Each homeowner purchases insurance (i.e. $q^*_{ict} > 0$) if:

$$\begin{aligned} f_{ict}(0) > 0 \quad &\iff \frac{p_{ict}}{1 - p_{ict}} > \left(\frac{r_i}{1 - r_i}\right)\left(\frac{u'(w_i)}{u'(w_i - L_i)}\right) \\ &\iff \frac{p_{ict}}{1 - p_{ict}} > \left(\frac{r_i}{1 - r_i}\right)\left(\frac{1}{\exp(R_i L_i)}\right) \end{aligned}$$

The first line follows directly from the homeowner First Order Condition. The second line assumes CRRA utility. R_i is the coefficient of risk aversion. If we define a random

[1] By the Implicit Function Theorem (IFT) we can write $\frac{\partial q^*_{ict}}{\partial p_{ict}} = -\frac{\partial f / \partial p_{ict}}{\partial f / \partial q^*_{ict}}$, where f is: $f(q_{ict}, w_i, l_i, r_i, p_{ict}) \equiv p_{ict}(1 - r_i)(w_i - l_i - r_i q_{ict} + q_{ict}) * u' - (1 - p_{ict}) r_i * u'(w_i - r_i q_{ict}) = 0$. Note that the comparative static does not depend on the functional form of f other than the restriction that two conditions on f must hold. First, Equation (2) must be continuously differentiable at (q^*_{ict}, p_{ict}), given the values of the fixed parameters w_i, l_i, r. Second, $\partial f / \partial q^*_{ict} \neq 0$ at (q^*_{ict}, p_{ict}).

variable $v_i = (\frac{r_i}{1-r_i})(\frac{1}{exp(R_i L_i)})$ and assume that $v_i \sim H$, then we can write the fraction of homeowners that take-up flood insurance in community c in year t as $H(\frac{p_{ct}}{1-p_{ct}})$, where H is an arbitrary distribution.[2] Consider a log linear approximation of $H(\frac{p_{ct}}{1-p_{ct}})$ where:

$$ln \left[H_{ct} \left(\frac{p_{ct}}{1-p_{ct}} \right) \right] \approx \alpha + \beta_t lnp_{ct} + \alpha_c + \gamma_{st} + \epsilon_{ct} \tag{3}$$

β_t is the estimated coefficient for the log flood probability in community c in year t. α is an intercept that doesn't depend on either community or time, while α_c is a community specific intercept (fixed effect) and γ_{st} is a state by year fixed effect.[3] [4] Recall that event study estimation Equation (1) is equivalent to the above linear approximation, except that I replace lnp_{ct} with a set of indicator variables for the timing of a PDD flood.

B National Flood Insurance Program

The flood insurance take-up model assumes that homeowners have the choice of whether or not to purchase insurance both before and after a flood. There are 6 institutional considerations that merit a more detailed discussion than space permits in the text of the paper.

B.1 NFIP Community Participation

Residents of a community can only purchase flood insurance if their community participates in the NFIP. Community participation in the NFIP is not mandatory and requires that a community commit to following certain flood plain management principals (e.g. building materials and structural designs). If a community does not participate in the NFIP, residents of the community are not able to avail themselves of some other federal programs (e.g. Department of Veteran Affairs loan guarantees, and grants to rebuild after a Presidential Disaster Declaration). The NFIP Status Book (current as of March 17, 2013) lists 21,899 participating communities and 2,118 communities not participating. Many of the non-participating communities have no land within the 100 year flood plain and thus have a relatively low flood risk.

In the early years of the NFIP, the official FEMA flood map (FIRM) was not created by the Army Corps of Engineers until a community had officially joined the NFIP. After a community joined the NFIP, but before a community's FIRM was created, a community was considered to be part of the NFIP Emergency Program. Once the FIRM was completed

[2] v_i varies at the homeowner level based on the location and size/type of the house (which determine r_i and L_i), and homeowner wealth and risk aversion (w_i and R_i).

[3] This assumes a Log-Log relationship between flood insurance take-up and the belief of a future flood. One implication of this linear approximation is that it restricts the log probability of a flood to be proportional to the log flood insurance take-up.

[4] I also considered the inclusion of higher order terms $lnp(\delta)^2_{ct}$ and $lnp(\delta)^3_{ct}$ as part of the log linear approximation. The Adjusted F Statistic for the estimation of Equation (3) is consistently larger without the squared and cubed terms.

the community joined the Regular Program. While in the Emergency Program residents have access to more limited levels of flood insurance coverage at lower rates. See Wright [2000] for a more complete discussion of the early years of the NFIP and the Emergency Program.

Both the 1990-2007 and 1980-2007 panels exclude communities that have not joined the NFIP at least one year before the start of the panel. The estimation results are insensitive to this restriction. I run a number of robustness checks that either drop this restriction completely, or vary the number of years a community must be in the NFIP before being included in the panel. (see Appendix Section E and Table 5 column (2) for one such robustness check).

B.2 Insurance Purchase: Private Companies or Directly from NFIP

Flood insurance deductables, insurance limits, and premiums are set by the NFIP. Initially all flood insurance policies had to be purchased directly from the NFIP. However, starting in 1983 homeowners could purchase flood insurance from private insurance companies through what is known as the Write-Your-Own (WYO) program. Since 1983 insurance policies could be purchased directly from the NFIP or from a private insurance company participating in the WYO program. The WYO program allows private companies to write and service flood insurance policies. Since private companies can't compete over price or insurance terms, they are compensated through an "expense allowance". A load factor of approximately 30-40 percent is placed on top of "actuarial" rates to cover the expenses of running the NFIP (e.g. creating the flood maps, paying damages, and compensating the private WYO insurance companies). The vast majority of insurance policies are transacted by private insurance companies. Michel-Kerjan [2010] provides a more complete discussion of the WYO program.

From the perspective of the homeowner, there is no difference between whether the policy is purchased from a private insurer or directly from the NFIP. All insurance policies must be renewed annually or the policy will be dropped. The NFIP bears all of the risk and is responsible for paying homeowners for insured losses.

B.3 Mandatory Purchase Laws

The federal government created the National Flood Insurance Program (NFIP) in 1968. An amendment from 1973 to the NFIP established two mandatory purchase laws. First, homeowners with federally insured mortgages whose residences are in Special Flood Hazard Areas (i.e. the 100-year flood plain) are required to maintain flood insurance. Second, individuals who receive federal assistance after a flood are also required to purchase insurance. In 1994 another amendment was passed that sought to strengthen the 1973 mandatory purchase amendment. A number of government sponsored and academic studies have examined the mandatory purchase provisions (e.g. GAO [1992]; FEM [1995]; Kunreuther [1996]; Browne and Hoyt [2000]; Tobin and Calfee [2005]; Dixon et al. [2006]). All have concluded that the mandatory purchase provisions are not widely enforced. Phone and email correspondence with officials who administer the NFIP have also underscored this same conclusion.

Unfortunately, program-wide detailed enforcement data on the mandatory purchase provision are unavailable. One reason for this is that until very recently the NFIP did not retain information on individual insurance policies that identified the policy-holder as residing inside or outside the 100-year flood plain. Likewise, until very recently the NFIP has not attempted to maintain a database that lists all of the insurable structures inside (or outside) the 100-year flood plain. Without knowing which properties *might* be subject to the first mandatory purchase law it is not possible to know which properties *should* have insurance under the law. Finally, the NFIP doesn't have access to mortgage information that would distinguish between properties inside the 100-year flood plain that *should* be required to have flood insurance.

I use the GAO survey data (GAO [1992]) to examine the first mandatory purchase provision and calculate that only about 3% of the policy-holders purchased a policy because they were forced to do so. Thus, the paper's insurance purchase model is applicable to 97% of the households with flood insurance policies. The model also describes the purchasing decision faced by more than 99% of potential buyers residing within the 500-year flood plain. The GAO survey data are among most detailed and comprehensive available. The GAO report has the benefit of being released roughly in the middle of the 1980-2007 estimating panel. Details of this calculation are provided in Appendix Table 1.

FEM [1995] discusses a FEMA study that analyzes compliance with the 2nd Mandatory Purchase requirement from the 1973 amendment. Only 7% of a sample of homeowners who received federal assistance after one of 10 PDD floods (sample size 679) have a flood insurance policy three years after the flood. This 7% "compliance" rate is almost certainly an over-statement, as many of these homeowners would have chosen to purchase insurance without the official obligation to do so.

B.4 Flood Insurance Prices

Appendix Table 2 shows the change in annual insurance premiums for actuarial rate-based (column 1) and grandfathered (column 2) properties for the 10 year period from 1996-2005. Panel A provides the annual rate changes, while Panel B provides summary statistics. For example, the first row of Panel A is for 1996. In this year the premium charged for actuarial rate-based properties declined by 0.9%, while the premium for grandfathered properties increased by 6.7%. Overall, average premiums increased by 0.61% for actuarial rate-based properties and by 1.49% for grandfathered properties. The annual premiums are equally likely to increase as they are to decrease for the grandfathered properties, while premiums are slightly more likely to increase for actuarial rate properties.

The NFIP yearly premium adjustments for the years 2001-2005 are documented in the Actuarial Rate Review documents found here: `http://www.fema.gov/business/nfip/actuarial_rate.shtm`. The NFIP provided spreadsheets of the rate increases (available on request) for the years 1996-2000. The nominal NFIP rate adjustments are converted to real rates of change using the Consumer Price Index (CPI) for each year. The CPI table used for inflation adjustments can be found here: `ftp://ftp.bls.gov/pub/special.requests/cpi/cpiai.txt`. The yearly premium adjustments are not available separately for the last two years of the insurance panel (2006 and 2007) or before 1996. The NFIP does provide an estimate of the average nominal percent rate increase across the two classes of properties for the last two years, which after adjusting for inflation, are: 2006 (0.9%) and 2007 (3.2%). NFIP personnel have assured me that this period is representative of the program's pricing history.

B.5 Number of Insurance Policies-in-Force

The number of policies-in-force is an extensive margin measure of insurance demand. An alternative is to use the quantity of insurance purchased (intensive measure). Using the number of policies in force avoids several theoretical and empirical challenges that are involved with using quantity of insurance purchased.

First, focusing on the number of policies-in-force provides an unambiguous prediction that doesn't depend on the level of risk aversion (only that individuals are risk averse). If the expected flood probability increases then the marginal homeowner who was previously just unwilling to purchase flood insurance will now purchase insurance (i.e. $dq/dp > 0$ by the Implicit Function Theorem). This is true for any level of deductible choice.

The NFIP has an insurance limit of $250,000 for the insured structure and $100,000 for personal property. The insurance limit almost certainly implies that some homeowners would prefer to purchase more insurance than they are allowed to purchase by law. However, this does not effect whether a homeowner would purchase a non-zero amount of insurance.

Second, the deductible and the coverage limit are critical when considering quantity of insurance purchased. Using quantity of flood insurance purchased requires understanding how individuals trade-off a lower deductible vs. a higher level of coverage when the perceived probability of a flood changes. Modeling this trade-off requires particular attention to implied levels of risk-aversion (Chetty [2006]; Sydnor [2010]). Unfortunately, data on deductibles and coverage levels are jointly unavailable from the NFIP at the individual-level for the time period considered in the paper. The coverage limit also complicates use of the quantity of flood insurance purchased as a measure of learning because it is very likely that some policy owners are forced to purchase less insurance than desired. It would be difficult to "correct" (via estimation or simulation) the top censored insurance purchase amounts because non-aggregated individual-level data are not available from the NFIP for this time period.

B.6 Fixed Flood Probability Assumption

Changes to the geographic landscape can alter water-runoff and absorption. Almost by definition this would change potential flood patterns. Early NFIP literature acknowledges this very possibility (e.g. FIA [1976]). This paper uses *very large* floods for identification and assumes that the probability of these large floods is constant during the estimation time panel. The question is how significant are these man-made changes to the landscape for changes in the incidence of *very large* floods?

The Army Corps of Engineers collect and analyze historical storm, rainfall, and landscape engineering data. These data are used to created flood probability tables. NFIP actuaries then set insurance prices based on the flood probability tables (scaled up by a loading factor to reflect the costs of running the program). Most flood maps were constructed from the mid-1970's to the early 1980's, and very few of these maps had any significant changes during the panel period.

Conversations with actuaries at the NFIP have confirmed the NFIP's view that new land development is thought to have, at most, only a very small impact on the incidence of large floods during this time period. New land development is more likely to effect the number of smaller floods, or the cost (not incidence) of the largest floods. Homeowners don't appear to update expectations based on differences in costs among the larger and smaller PDD floods (Section 4.1 of the manuscript). The econometric specification uses only PDD floods that would come from the far right tail of the flooding distribution. If, for example, there are more minor floods in a community due to new land development then it would be reasonable to expect that the overall level of flood insurance take-up to be larger. Recall that the goal of this paper is not to estimate the overall level of insurance take-up, but rather causal changes in insurance take-up after PDD floods. The econometric models (Equations (1) and (2) in the manuscript) uses to estimate the change in insurance take-up after a flood include community and state-by-year fixed effects that absorb differences in the overall level of flood insurance.

C Discussion of Serial Correlation in Floods

Flooding can occur for a number of reasons including: a large amount of rainfall over a short time period that overwhelms the manmade and natural water absorbtion capacity of the community, a coastal ocean storm surge, and rivers exceeding their water storage capacity and overflowing their banks. To evaluate whether serial correlation in large annual floods might explain observed insurance take-up I first highlight some of what is known regarding serial correlation in river water storage (water height) dynamics, and in annual weather events. I then test wether there is any evidence for serial correlation in flooding Presidential Disaster Declarations (this paper's measure of large regional floods).

Serial correlation in large annual floods might occur if a river is slow to return to historically normal water heights after having crested and flooded surrounding communities. It is well known that river water height and flow are correlated over short time periods such as weeks or months. Hurst [1951], Fiering [1967],and Fiering and Jackson [1971] were among the first scientists to study and model the correlation in river height and flow. Fiering [1967] (page 4) writes: "far and away the most significant of the recent contributions is the recognition of persistence among successive flows values and, consequently, among system outputs. Monthly and seasonal flows demonstrate a high order of persistence, reflected by large correlation coefficients between flows in successive time periods." More recently, Lettenmaier et al. [1994] examine a panel of water flow data for US rivers during the forty year period 1948-88 and find evidence of monthly correlation in water flows.

Serial correlation in annual large floods might also occur due to correlation in above average annual rainfall that could potentially lead to each of the above proximate causes of a flood. El Nino and La Nina-Southern Oscillations (collectively referred to as ENSO) are two large global weather phenomena associated with above or below average annual levels of precipitation for many regions of the US. For example, according to the National Oceanic and Atmospheric Administration (NOAA), El Nino is associated with more severe winter flooding in many west coast states (http://www.wrcc.dri.edu/enso/ensofaq.html\#11), while at the same time associated with fewer Altantic-based hurricanes (http://www.pmel.noaa .gov/tao/elnino/faq.html\#hurricanes). An ENSO event is defined by a warming (El Nino) or cooling (La Nina) of the average surface water temperature of the east-central area of the Pacific Ocean by at least half a degree Celsius. From 1950-2000 there were 21 ENSO events (http://ggweather.com/enso/years.htm). El Nino, for example, tends to occur every 3-7 years. Nevertheless, predicting the occurrence of either El Nino or La Nina more than a few months in advance (once Pacific water temperature changes begin to be observed) is notoriously difficult (http://www.elnino.noaa.gov/research.html). Importantly, there is no evidence in favor of a positive annual correlation between El Nino (or La Nina) events (Fedorov et al. [2003]).

Testing Independence of Regional Floods

I use two statistical tests to evaluate the Null Hypothesis that annual floods are independent events during the 18-year time period of the main event study panel (1990-2007). The first statistical test is the Wald-Wolfowitz Runs Test (Swed and Eisenhart [1943]). The Wald-Wolfowitz Runs Test is a non-parametric test that tests the assumption that PDD floods are independently and identically distributed for each county. Importantly, this test does not assume that the probability of a flood in each county is the same. Instead, the length and number of sequences (i.e. "runs") for each county are used to test whether floods occur in consecutive years more often than would be expected. A Runs Test on the sample of 1990-2007 panel counties with at least two PDDs results in a p-value of 0.30. I fail to reject the null hypothesis of independence at all conventional significance levels.

The intuition of the test is that the annual time series of PDD floods for each county can be divided into "runs" of 1's and 0's, where a 1 indicates a year of a flood. A low number of runs for the county means that the floods are clustered together more than one would expect if floods were random yearly draws from some underlying distribution. The Runs Test results in a z-score for each county. Squaring the number of county z-scores and then summing the squared z-scores results in a Chi-Square distribution with degrees of freedom equal to the number of counties. In the above test, there are 2253 degrees of freedom and a test statistic of 2286.82.

The second statistical test for autocorrelation of floods is a simple Chi-Square in the spirit of Chamberlain [1982]. I test the hypothesis that annual floods are independently and identically distributed by examining flood event year windows that have exactly two PDD floods. I vary the length of the event year windows between 5 and 10 years. Each flood sequence is identified according to two criteria: (i) There is a PDD flood in the first year in the sequence, and (ii) there is exactly one other PDD flood before the end of the window. I consider whether there are more floods in the 2nd year of the sequence than would occur by chance given the assumed hypothesis. I test the hypothesis of independence for each window size using a Chi-Square test with one degree of freedom. The test considers the expected probability of having the 2nd flood event in the 2nd year of the sequence (consecutive flood years) verses not having the 2nd flood in the 2nd year. The same county is allowed to contribute multiple sequences for each of the window sizes. Finally, this test avoids one of the challenges in comparing the transition probability of being flooded conditional on a flood the previous year, with that of being flooded conditional on not having a flood the previous year. We expect a location that is flooded last year to be more likely to flood the following year because there is "selection" in being flooded. Those locations with observed floods are more likely to have a higher underlying probability to flood.

The results are displayed in Appendix Table 3. Columns (1) through (6) of the table display the test results for the windows of sizes 5 to 10 years. The first row provides the Chi-Square Test Statistic. The critical cutoff values for rejection of the null hypothesis of independently and identically distributed floods are 2.71 (10% level), 3.84 (5% level), and 6.63 (1% level). The 3rd row shows the expected number of consecutive floods under the null hypothesis. The 4th row shows the actual number of floods. The null of independence can be rejected for 4 of the 6 samples. However, in only one of the samples is there evidence that a flood is more likely to occur in the year following a previous flood. Three of the samples suggest that a flood is less likely the year after a previous flood. Overall Appendix Table 3 provides mixed evidence in support of the maintained hypothesis of independence, and no clear evidence that a flood is more likely to occur in the year following a previous flood.

D Data Sources

D.1 Flood Insurance Data

Policy Data

The flood insurance policy data are obtained from the National Flood Insurance Program (NFIP) as part of a Freedom of Information Act Request. The data are the complete record of NFIP flood insurance policies from 1978-2007 and include the following variables: US state, community name, community id, year, number of policy holders, total premiums collected, number of claims, and total amount of claims paid out. All flood insurance policy data are aggregated at the community level by the NFIP. The disaggregated (individual level) data are not available for this time period. The NFIP does not retain most of the policy-level insurance information. The reason is that the vast majority of flood insurance policies are handled by private insurers. The NFIP definition of a community is roughly equivalent to a Census Place, but NFIP community ids are not equal to Census Place fips codes. I thank Tim Scoville, NFIP Systems Development Manager, and Andy Neal, NFIP Actuary, for their assistance in providing and interpreting the data.

Community NFIP participation information is from the Status Book at the NFIP website: `http://www.fema.gov/fema/csb.shtm`. Variables from the Status Book include: date of community participation in the Emergency Program, date of community participation in the Regular Program, FHBM (map) date, FIRM (map) date, and community suspension date. Community flood risk information is calculated directly from community FIRMs. I received digital copies of community FIRMs for all communities with a digitized map as of May 2009. Approximately 25% of NFIP communities had a digital FIRM as of this date. I then used GIS software to extract information on the amount of land in each community that belongs to each type of FIRM flood zone. I define the following variables:

percent low flood (outside 500 year flood plain): equal to the sum of land area with 0.1 percent flood and 0.2 percent flood divided by the total community land area

percent medium flood (outside 100 year flood plain and inside the 500 year flood plain): equal to the sum of land zoned D or X divided by the total community land area

percent high flood (inside 100 year flood plain): equal to the sum of land zoned A or V divided by the total community land area.

<u>Map Data</u>

Appendix Table 4 displays summary information for the subset of communities in the primary sample with non-missing digital flood maps. Panel A lists the percent of a community that falls within each of the three flood map designations. The mean (median) percent of a community's land area that falls with the flood plain is 14 (8) percent. The vast majority of each community is within the Corps of Engineers estimated 500 year flood plain. The mean amount of each community falling outside the 500 year flood plain is just 4%. Panel B divides flood insurance take-up in 1980, 1990, 2007 by whether the community contains more than or less than the median amount of the community land within the (100 year) flood plain. Not surprisingly, the number of flood insurance policies per person is higher in those communities with more land in the flood plain. For example, in 1990 the mean number of policies in communities with more than the median amount (8%) of land zoned in the flood plain is 44, while those communities with less than the median have a mean of 4 policies.

D.2 Flood Data

<u>Presidential Disaster Declaration Data</u>

These data were downloaded from the Public Entity Risk Institute (PERI) at `http://www.peripresdecusa.org/mainframe.htm`. The data include: the Presidential Disaster Declaration number, type of disaster, date of declaration, US state and counties included as part of the disaster area, and a measure of disaster cost. I only consider disasters that list the type (source) of disaster as being: coastal storm, severe storm, hurricane, or flood. The 1980-2007 panel includes 805 distinct PDDs. The distribution over these years is: min = 2 (2nd fewest 11), max = 60, mean = 29, median = 26, standard deviation = 14. I thank Richard Sylves for helpful conversations regarding these data.

<u>PERI Cost Data</u>

The PERI measure of disaster cost is "the total amount of federal disaster relief [...] recorded in FEMA's records for the State, and this sum includes the state pass-through amount." The cost measure includes PDD disaster spending from both the Public Assistance and Individual Assistance programs. The Stafford Act of 1988 specifies that the federal government will cover at least 75% of the replacement value of infrastructure or building repairs. States are required to pay the remaining 25% as a condition of receiving the federal Public Assistance money. The costs also include (1) Mitigation spending ("post-disaster federal assistance calculated as a percentage [15%] total federal disaster relief paid out on a declaration"), (2) FEMA administrative expenses, and (3) Mission Assignment spending ("spending under which FEMA permits another agency working a president declared major disaster or emergency to draw funding") [source: PERI online data documentation]. All cost data are adjusted to 2007$ using the Consumer Price Index. There are two further qualifications in using the PERI cost data. First, the data are aggregated by PDD at the state-level. Second, the variable doesn't include any continuing costs that are incurred after April, 2008. The PERI website has detailed documentation regarding the PERI cost data.

<u>FEMA Public Assistance Data</u>

The Public Assistance data include all claims made to FEMA by public entities and non-profit groups for damage to infrastructure and buildings from 1990-2007. There are more than 800,000 PDD flooding related damage claims filed with FEMA during this time period. The claims data include damage location, damage amount, damage date, and the PDD number for the event that caused the damage. I link the Public Assistance data to the PERI Presidential Disaster Declaration information using the PDD number. I use the hand entered damage location address to identify NFIP communities that are flooded (i.e. "hit" by a PDD flood that occurs in the county). I am able to determine the community name for 98.6% of the Public Assistance damage claims. I almost certainly fail to identify some communities as being "hit" by a PDD flood for some of the events. The practical consequence of this miscoding will be to bias the event study estimation results for the 1990-2007 panel towards zero (assuming that there is a positive correlation between being hit by a flood and take-up). Cost data are adjusted to 2007$ using the Consumer Price Index. The Public Assistance data were received as part of a Freedom of Information Act request. I thank Deni Taveras and Paul Weschler for their assistance in providing the Public Assistance data.

<u>SHELDUS Flood Cost Data</u>

I collected SHELDUS flood cost data, but decided **not to use these data** due to a serious concern regarding the consistency of the data. Here I briefly outline the basis of concern.

Spatial Hazards Events and Losses Database for the United States (SHELDUS) is a database that includes county-level cost estimates for natural disasters in the US from 1960-2007 (`http://webra.cas.sc.edu/hvri/products/sheldus.aspx`). Although SHELDUS includes data from multiple sources, the primary source of cost data is from National Weather Service NCDC monthly Storm Data publications. A critical feature of The National Weather Service data is that they are self-reported by individual weather stations.

One consequence of the self-reporting is that the NCDC monthly Storm Data publications, and by extension SHELDUS, are susceptible to bias from unreported (i.e. "missing") data. In the case of flooding, the challenge due to missing cost data is severe enough to render the SHELDUS data completely inadequate as a source of cost data for this paper.

In April 2009 I downloaded county disaster cost data for the years 1960-2007 for four SHELDUS hazard types: flooding, hurricane, severe storm, and tsunami. These flood designations correspond to the same designations as those for Presidential Disaster Declarations. In fact, SHELDUS also provides an option to select county costs by PDD number. However, just 99 of the 1151 PDD flood events (8.6%) from 1960-2007 are labeled in SHELDUS. In addition, many of the counties included as part of the 99 PDD events are listed in SHELDUS as having no flood damage. This is completely implausible. Governors of states submitting PDD requests are required to document flood damage in counties being included as part of the PDD request. The missing county costs in SHELDUS also contradicts documented flood damage by FEMA as part of the Public Assistance program.

In April 2009 I had multiple conversations with Chris Emrich who is a researcher who assisted in compiling SHELDUS. In Emrich's view SHELDUS is the best and most comprehensive disaster cost database available, but that it is also incomplete. Emrich agreed with my assessment that in the case of floods the most reliable flood cost data would be FEMA data collected as part of the PDD floods.

Community Rating System Data

"The NFIP Community Rating System (CRS) was implemented in 1990 as a voluntary program for recognizing and encouraging community floodplain management activities exceeding the NFIP's minimum standards" (FEM [2007a], p1). As of 2007, fewer than 5% of NFIP communities participated in the CRS program (FEM [2007a]). Communities receive CRS points for community-wide activities that range from mapping and regulatory activities to flood preparedness activities (FEM [2007b]). The CRS data used as a robustness check in Section 4.1 of the paper were received directly from FEMA. FEMA provided me with a spreadsheet of data of annual NFIP community participation in the CRS program and accumulated CRS points by year for the years 1996-2010. The paper uses only the years 1996-2007 (to match the flood and flood insurance data). Appendix Table 7 presents the event study specifications that use the CRS data. Section 4.1 of the paper and Section E.6 summarize the results of Appendix Table 7. FEMA asked that I not make public the raw CRS data. I thank Bill Lesser (FEMA) and Leslie A. Bond (Bond Associates) for their assistance in providing and interpreting the data.

D.3 Neighbor Designation Data

Adjacent Counties

There are two sources for the geographic distance data. Adjacent county information is from the Inter-University Consortium for Political and Social Research (ICPSR) *Contiguous County File, 1991* (*www.icpsr.umich.edu*). The *Contiguous County File, 1991* defines an adjacent county as sharing a boarder, being connected by a major road, or connected due to "significant economics ties." I only consider adjacent counties to be those that share a border.

Centroid Counties

The distance-based neighboring county lists were created by measuring the Euclidean distance between county centroids using Quantum GIS software. To improve accuracy in measuring large-scale (small area) distances, the centroids of US counties were projected from spherical geographic coordinates (latitude & longitude) onto a planar surface. The original US county shapefiles from the US Census Bureau's TIGER (Topologically Integrated Geographic Encoding and Referencing) database were set in the North American Datum 1983 (NAD83) geographic coordinate system. We used a projection based on the same datum (with a secant conic surface). ArcMap software was used to project the shapefiles.

A previous draft of this paper used county distance measurements from unprojected shapefiles to determine the list of closest county neighbors. The use of the unprojected shapefiles leads to county neighbor lists that are somewhat different. Using the lists from the unprojected shapefiles in the event study regressions of Figure 8 (and Appendix Tables 8-13) lead to point estimates that are both less economically and less statistically significant for the centroid neighbors. Finally, as a robustness check we projected the county shapefiles using several other geospatial specifications. The results of Figure 8 (and Appendix Tables 8 to 13 are very similar across alternative (projected) specifications.

Media Market Counties

The Media Market data are defined by Nielson Media Research. Every US county or county equivalent is assigned a primary television media market called a Designated Media Market (DMA). The DMA county designations are periodically reevaluated by Nielson Media Research. Nielson Media Research released new county DMA designations in 1970, 1972, 1980, 1990, and 2000. Only about 5% of the counties switch primary DMA designations from 1980-2000. I use a conservative approach and consider a county to be in a DMA up until the year that the new designation is released. This approach will bias against observing a media market information effect if counties actually begin to receive the majority of the news information from the new DMA in one of the years prior to the official reclassification. I thank James Snyder for sharing the DMA data. The data were first collected and used by Ansolabehere et al. [2006] and Ansolabehere et al. [Unpublished Manuscript].

D.4 Population, Income, and Migration Data

Population Data

The paper's main dependent variable is annual flood insurance policies per capita. I divide the number of flood policies at the community level by the community population. The US Census Bureau creates adjusted annual population estimates for Census

Places from 1990-2007 using the Decennial Censuses and a variety of other data sources including information on the number of births, deaths, and housing units. See `http://www.census.gov/popest/archives/1990s/` for the data files and for more information on the Census-based estimates. The Census Bureau does not create annual Census Place estimates for the 1980s. For the years 1981-1989 I create my own Census Place population estimates. I linearly extrapolate using the 1980 and 1990 Census Place files. Note that I use annual information on community population, in part, because yearly community-level data on insurable structures (homes and businesses) are not available.

I also collected yearly county-level population data. The county population data are used to create the county per capita flood insurance variables used in the 1980-2007 panel. I also use these data to normalize the PERI disaster cost data. Annual county-level cost data from 1969-2007 were downloaded from: `http://seer.cancer.gov/popdata/methods.html`. For documentation: `http://seer.cancer.gov/popdata/popdic.html`.

Income Data

The annual county-level income data are derived from the US Census Bureau's Quarterly Workforce Indicators (QWI). "Compiled from administrative records data collected by a large number of states for both jobs and firms, and enhanced with information integrated from other data sources at the Census Bureau, these statistics offer unprecedented detail on the local dynamics of labor markets" (Abowd et al. [2005]). QWI files are made available through the Social Science Gateway (SSG) at Cornell University. The SSG is supported by NSF Grant #0922005. The QWI data can be downloaded by state here: `http://www.vrdc.cornell.edu/qwipu/R2011Q4/`.

The QWI files available through SSG include 30 different quarterly employment measures, all of which are tabulated by industry sector, and are further broken down by race and hispanicity (RH), sex and education (SE), or age by sex (WIA). We use the RH files, but collapse the data by quarter, industry, race, and hispanicity to derive a single annual statistic for each county for each of the 30 measures. For a detailed description of the QWI data please refer to Technical Paper No. TP-200-01 "The LEHD Infrustructure Files and the Creation of the Quarterly Workforce Indicators" (`http://lehd.did.census.gov/led/library/techpapers/tp$-$2006$-$01.pdf`).

Migration Data

The source of the county-to-county migration data is the Internal Revenue Service (IRS) Statistics of Income (SOI) division. According to the IRS, the "migration data for the United States are based on year-to-year address changes reported on individual income tax returns filed with the IRS." (`http://www.irs.gov/taxstats/article/0,,id=212683,00.html`) An IRS prepared document called "U.S. Population Migration Data: Strengths and Limitations" (author: Emily Gross), located at the above link, provides a helpful overview of the data. Although the data originate from the IRS county-to-county migration files, migration data for the years 1978-1982 and 1984-1992 are accessed through the Inter-University Consortium for Political and Social Research (ICPSR): `http://www.icpsr.umich.edu/icpsrweb/ICPSR/`. A ICPSR description of the data can be found here: `http://www.icpsr.umich.edu/icpsrweb/SAMHDA/studies/02937/detail`.[5] Note that the 1983 county-to-county migration data are not available. I thank Philippe Wingender for sharing these data. The data files were first collected and used by Serrato and Wingender [2011].

We define annual net migration as the difference between total in-migration and total out-migration, divided by the sum of the total number of non-migrants and total out-migration.

D.5 TV News Story Data

The media market local TV news story data were purchased from Teleclip, Inc. (`http://www.teleclip.com/`). Teleclip retains archived local news broadcast data for at least one national TV station affiliate (ABC, CBS, NBC, FOX) in the majority of the (Neilson Media Research defined) TV media markets. The exact number of media markets included in Teleclip's archives varies by year. 2003 is the first full year for which Teleclip's archives include representative stations for US media markets. As such, the sample of news story data is from 2003-2007 and cover the last 5 years of the two flood panels. The number of media markets covered by year (after restricting to national TV affiliates for ABC, CBS, NBC, and FOX) are: 103 in 2003, 125 in 2004, 141 in 2005, 153 in 2006, and 157 in 2007. We only include media markets in the analysis if the media market is included in the database for the entire year. The exact names of the media markets covered each year are available on request.

We consider two different media market samples. First we consider the sample that includes all qualifying media markets for each calender year. Second we consider a balanced media market sample that only considers those media markets that are covered in each of the 5 years. In both samples we separately calculate the mean number of flood stories by year for media markets that have a PDD flood and those that do not have a PDD flood. Importantly, most media markets alternate between PDD flooded and non-PDD flooded status throughout the 5 years. This allows us to take advantage of both the within media market and the between media market variation in news story coverage.

The sample of flood-related news stories is determined by a text-based search of the transcriptions of the news broadcasts using the following search criteria:"flood*" AND ("presidential disaster declaration" OR "presidential declaration" OR "disaster declaration"). This text search is a conservative approach to identify PDD flood stories. The reason is that these search criteria also pick up on stories about flood events where: (i) the the governor of a state petitions the federal government for Presidential Disaster Declaration status and is turned down, or (ii) when there is a state disaster declaration. These other two classifications of a flood would generally include smaller, less costly floods. We separately calculated the number of flood stories using both the original text-based search results, and the original search results that exclude flood types (i) and (ii).

[5] Recommended citation: U.S. Dept. of the Treasury, Internal Revenue Service. County-to-County Study Files, 1978-1992: [United States] [Computer file]. ICPSR version. Washington, DC: U.S. Dept. of the Treasury, Internal Revenue Service [producer], 1998. Ann Arbor, MI: Inter-university Consortium for Political and Social Research, 2000. doi:10.3886/ICPSR02937).

In some media markets there is more than one TV affiliate included in the archived database. The flood story count data are weighted by the number of stations in each media market. The news story data include information on: date and time of broadcast, title of program (e.g. "Late Night News"), source, national network affiliation, media market, market size rank, and a text excerpt of the broadcast. I thank Geof Sloan for his assistance in providing and interpreting the data.

E Panel Construction and Robustness Checks

I construct the 1990-2007 and 1980-2007 balanced calendar time event study panels by first including all communities in the continental US for which I have a complete panel (18 or 28 years respectively) of flood insurance and community population data. Since the NFIP community ids do not match Census Place ids I am forced to match the communities using community name and state. Community names sometimes change, or are written/abbreviated differently in the NFIP and Census files. In addition, it is not always the case that an NFIP community corresponds to the same political boundaries as a Census Place. For example, I am from a coastal town Hampton, NH. Hampton includes a beach district called Hampton Beach. The US Census Place is Hampton. The NFIP community could be either Hampton or Hampton Beach. I only include NFIP communities in the sample if I am certain that the Census population data are from a political jurisdiction that exactly matches that of the NFIP community. I am able to match 70.4% of the NFIP communities with yearly Census Place population data.

I also make one data transformation and one additional sample selection decision. I limit the 1990-2007 and 1980-2007 balanced calendar time panels to include only those communities that were participating in the NFIP by the year before the start of each panel. This ensures that home and business owners are able to purchase flood insurance each year during the panel and that the first year that insurance was available for purchase occurs before the start of the panel. Finally, there are a small number of panel observations where a community has zero flood insurance policies in a particular year. I transform the flood insurance data by artificially assuming that there is one insurance policy for these communities in these years. This is necessary in order to take the natural log. The robustness of these panel modeling decisions is examined in greater detail in Appendix Tables 5 and 6.

E.1 Panel Construction

Appendix Table 5 examines how sensitive the preferred 1990-2007 panel event study specification (Figure 2) is to decisions regarding the construction of the panel. The table contains 6 columns each of which is a different regression. Column (1) reduces the baseline sample by excluding communities in counties without a PDD flood from 1990-2007. This specification drops 582 communities from the analysis (5.4% of the sample). The point estimates for the post flood event study that excludes communities without floods are insensitive to this panel restriction (the point estimates differ by 0.1 to 0.3 percentage points).

Appendix Table 5 column (2) restricts the sample to communities that were in the NFIP by 1980. Residents in these communities have a period of 10 years to first purchase flood insurance before the beginning of the event study. This restriction excludes 590 communities from the sample. The baseline specification includes communities that were part of the NFIP by 1989. The potential concern is that there could be accelerated take-up of flood insurance in the year(s) immediately after flood insurance becomes available for the first time. The coefficient estimates are insensitive to this panel restriction.

Appendix Table 5 column (3) changes how the event study coefficients are normalized by including the indicator variable for a year before a flood and excluding the binned indicator for the beginning of the event study. The interpretation of column (3) is now relative to 11-17 years before a flood. The point estimate for 11-17 years before a flood is slightly lower than for one year before a flood, and as such, the post flood coefficients are slightly higher. All of the coefficients are shifted up by about 0.5 percentage points.

Appendix Table 5 column (4) changes the dependent variable to levels. The take-up of flood insurance is positive and significant at the 5% level up to 8 years after the flood. The point estimate for one year after a flood implies that there are 7 more policies per 1000 residents relative to the year before a flood.

Appendix Table 5 column (5) considers how the precision of the estimates change when the standard errors are clustered to control for spatial correlation as proposed by Driscoll and Kraay [1998]. The standard errors do not change much as compared to those in Figure 2 in the manuscript. The only change in statistical significance is for 10 years after a flood, which is significant at the 10% level using the Driscoll-Kraay standard errors (and not significant at the 10% when the standard errors are clustered at the state level as in the text).

Appendix Figure 1 shows insurance take-up point estimates from the same specification as Figure 4 in the manuscript, except that the end points of the event study are not binned. The effect peaks at 9% one year after a flood. 27 years after a flood the point estimate is -2% (not statistically significant). The last post-flood year that insurance take-up is statistically significant is 15 years after a flood. The implied slope of post-flood insurance take-up (the "impulse response function") is fairly consistent over the 27 post-flood years. The main reason for binning is to preserve statistical power. The primary panel is balanced in calender time (not event time) so there are many fewer floods contributing to the identification for the lags and leads at the ends of the event study. The second reason is for presentation. The 15-year window is a (more) manageable set of results to display graphically and in tables.

E.2 Sequential Floods

The baseline event study specification (Equation (1) in the text) includes one set of event time indicators. No distinction is made between the sequence of floods for a community during the estimating panel. Appendix Figure 3 plots event time insurance take-up coefficients from estimation of a version of Equation (1) that separately measures the effect of the 1st (circles) and 2nd (squares) flood hits using the 1990-2007 Panel. The bars show the 95% confidence intervals. There are 10,841 communities in the panel, of which, 6,914 are hit by at least one flood and 3,822 by at least two floods. The point estimates for insurance take-up are about two percentage points larger for the 1st hit in the 5 years after a flood, but the difference is not statistically significant. After 5 years the point estimates are very similar.

E.3 Homeowners in Low and High Migration Counties

There is no evidence that insurance take-up after a flood is larger in high migration counties. Figure 2 plots event time insurance take-up coefficients from the estimation of a version of Equation (1) that separately measures the effect on homeowners living in low (circles) and high (squares) migration counties. The bars show the 95% confidence intervals. There are two differences between this specification and the baseline estimation of Equation (1) using the 1980-2007 Panel shown in Figure 4 of the text. First, a low (high) migration county is one that is below (above) median among all counties in our sample based on the average county migration rate from 1984-2007. Two sets of event time indicators are included in the specification to separately measure the effect for homeowners in above and below migration counties. Second, county migration data are only continuously available for the years 1984-2007, so the panel is restricted to the years 1984-2007.

E.4 Hurricane Katrina

Hurricane Katrina hit the Gulf Coast of the US in 2005. The impact of the flooding from Hurricane Katrina in terms of damage, loss of human life, and migration is very different from every other flood in our sample (e.g. Groen and Polivka [2010]). Hurricane Katrina should not be thought of as a representative example of a PDD flood. The event study results are insensitive to the inclusion of Hurricane Katrina and the 2005 Hurricane season. I test the sensitivity of the baseline event study insurance take-up results two ways. First, I drop all communities in Louisiana from the event study. The post-flood take-up coefficients differ from the baseline event study by at most 0.3 percentage points (and not always in the same direction). There is no change in statistical significance. This specification is shown in Appendix Table 5 column (6). A specification that excludes both Louisiana and Texas (not shown) differs from the baseline by between 0.1 and 0.7 percentage points (and not always in the same direction). Second, I shorten the 1990-2007 and 1980-2007 panels (not shown) to exclude the last three years of the panel (the year of Hurricane Katrina and the subsequent two years). The overall pattern remains unchanged. The post-flood take-up estimates are shifted up about one percentage point in both shortened panels relative to the baseline results.

E.5 Changing Homeowner Income

Changing levels of wealth might affect purchase of flood insurance. We test the sensitivity of the results to changing levels of *income* using the 1980-2007 panel. Income is used as a (imperfect) proxy for wealth. To test the sensitivity of the results to changing levels of income we include yearly county income as a control in the baseline event study analysis. The annual county-level income data are derived from the US Census Bureau's Quarterly Workforce Indicators (QWI). Recall that Equation (1) in the text includes community fixed effects, and thus controls for constant differences in wealth between communities.

Controlling for yearly county income changes the estimated event study coefficients for insurance take-up by at most 0.1 percentage point. The estimated coefficient on the income variable is economically very small and not statistically different from zero. Results available on request. We conclude that changing homeowner income at most accounts for only a tiny fraction of the observed insurance take-up.

E.6 Community Protective Measures

Appendix Table 7 considers two event study robustness regressions using the Community Rating System (CRS) data. The CRS data are a measure of changes in community-wide flood protective measures. Column (2) controls for an indicator for CRS community participation (extensive margin). Column (3) includes a variable for the number of points earned (intensive margin). The number of points is a proxy for the scale of the protective measures. Columns (2) and (3) are otherwise identical to Equation (1) in the paper except that they are run on the 1996-2007 panel with year fixed effects. Column (1) displays the coefficients from the event study regression without either CRS control.

The CRS participation indicator is positive and statistically significant in column (2). This suggests that communities with greater community-level flood protective measures have more insurance (not less, as the protective measure hypothesis would suggest). It should be noted that the CRS participation variable is identified off of just 112 of the 9,607 communities in the panel (i.e. those that change CRS participation status). Column (3) includes the CRS points variable. This variable is economically small and statistically insignificant.

E.7 Balanced Event Time

Appendix Table 6 estimates a version of Equation (1) on 4 different panels each of which is balanced in event time. Each regression contains many fewer communities and observations as compared to the event study specification that is balanced in calendar time. The reason for this is that most communities are flooded multiple times. Due to the limited power (and degrees of freedom), all 4 regressions include calendar year fixed effects rather than the more flexible state by year fixed effects. We might expect that the post flood coefficients to be about 2-3 percentage points lower with state by year fixed effects (this is the case for the balanced calendar time panel). Columns (1) and (2) use the timing of a flood hit to define the panel. In column (1) a community is included in the panel only if it is hit by a flood and has 5 pre- and post- years with no flood hit. Only event time years $\tau \in [-5, 5]$ are included in the event study. The earliest calendar year included is 1985, since this is 5 years before the first year in which I can determine whether a community is hit by a PDD flood. Note that I can only measure whether a community is hit by a PDD flood beginning in 1990, but I can use the existence of PDD floods to know with certainty that a community was not hit by a flood from 1985-1989. 3,195 of the 3,431 communities are hit by one flood, while 235 communities are hit by two floods and one community is hit by three floods (separated by 5+ years). Column (2) considers communities with a least 10 years before and after a flood hit. All 934 communities are hit by exactly one flood and contain 21 observations ($\tau \in [-10, 10]$). Columns (3) and (4) are similar to the first two columns except that I use a PDD flood, and not whether you are hit by the flood, to define the sample. In column (3) only event time years $\tau \in [-5, 5]$ are included in the event study. 2,905 of the 3,532 communities are in counties with one PDD flood, while 589 are in counties with two floods and 38 are in counties with three floods (separated by 5+ years). In column (4) there are 590 communities, each in a county with one PDD flood and 10 years before and after with no PDD floods. All of the communities in column (4) contain 21 observations ($\tau \in [-10, 10]$)

All 4 of the balanced event study panels in Appendix Table 6 confirm the same pattern in flood insurance take-up as evidenced by the larger balanced calendar time panels discussed in the text of the paper. There is a spike in take-up immediately after a flood and there is no pre-flood trend in insurance take-up. The spike in insurance take-up in column (2) is about twice as large as in column (1). Similarly, the spike in take-up in the 10-year window for PDD floods (column 4) is about twice that for the 5-year window (column 3). One explanation for the difference in the take-up of insurance immediately after a flood is sample selection. A flood for a community with only one PDD flood in 21 years is likely to contain more information and be more of a "surprise" than for communities with more frequent floods.

E.8 Neighbor Floods

Varying Geographic (Accumulative) Distance

Appendix Table 8 shows the post-flood event time coefficients for flooded communities and neighbors to flooded communities for 6 separate regressions using Equation (2). The only difference between each of the 6 regressions is the definition of a non-flooded community neighboring a flood. Columns (1)-(4) consider a neighbor to be a community in the 1,5,10, and 20 geographically closest counties to a PDD county. Column (5) defines a neighbor as a community in a county adjacent to a PDD county. Column (6) defines a neighbor as a community in a county that shares the same television media market. Each regression includes state by year fixed effects.[6] Panel A shows the take-up coefficients for communities that are in PDD flooded counties. These coefficients are very similar both across the 6 columns and as compared to the coefficients in the regression that doesn't include any neighbor event time indicators (Figure 4 in text).

Panel B shows the coefficients from the 6 different definitions of a community flood

[6] The state by year fixed effects flexibly control for state and calendar year time that might be correlated with flood insurance take-up. However, these fixed effects exclude cross-state geographic neighbor and media market identification (shown to be an important source of variation in Figure 7 in the paper). For this reason, the regressions in Figure 8 from the paper and the 6 Appendix Tables that examine take-up in neighboring communities (Tables 8-13) use slightly larger end bins to improve statistical power without changing the interpretation of the coefficients of interest.

neighbor. Column (1) displays the take-up coefficients for those communities in the closest county not declared a PDD county. These communities could be thought of as the marginal communities just outside the worst flooded counties. Not surprisingly, the duration of the insurance take-up response is similar to those communities in the PDD counties, although the size of the point estimates are only about one-third as large. Columns (2)-(5) consider more expansive definitions of a geographically neighboring community. The surprising message from these regressions is that even as the definition of a flood neighbor expands to include communities farther away from the PDD flooded counties, insurance take-up is still statistically significant for up to 5 years after a flood. The point estimates range from 1.5% to 2.6%. In fact, the the statistical significance is greatest for columns (3) and (4) which include the communities that are most distant from the flood.

Panel B Column (6) considers the media market definition of a flood neighbor. The point estimates are statistically significant at the 1% level for up to 5 years after a flood and range from 2.8% to 3.6%. Interestingly, since there are 212 media markets and approximately 3,000 US counties, a rough estimate of the median number of counties per media market is 15. Selecting the closest 10 and closest 20 geographically neighboring counties is one way to bound the approximate spatial size of a media market. One possible explanation for the increased statistical significance of the geographic neighbors in these two regressions is that they are picking up on the effect of being in the same media market. This explanation is explored further in Appendix Tables 9 and 10.

Appendix Table 9 displays coefficients from the same insurance take-up regressions as Appendix Table 8, except that the media market flood neighbor indicator variables are included in each of the model specifications. The 5 columns correspond to 5 separate regressions, each of which includes a different set of flood neighbor indicator variables. Panel A shows the post-flood coefficients for the media market flood neighbors. The point estimates are statistically significant at the 1% level for the first 5 years after the flood regardless of the definition of geography used for the geographic neighbor. The point estimates range from 2.4% to 3.5% and are remarkably consistent across the specifications in the table and with those from the specification that doesn't control for a geographic neighbor (Appendix Table 8, column 6).

Appendix Table 9 Panel B shows the post flood insurance take-up coefficients for the geographic neighbors. Column (1) again considers those marginal communities that are in the very closest non-PDD counties. There is a similar pattern of take-up for these communities as in column (1) of Appendix Table 8, except that the statistical significance is lower for the coefficients during the first 5 post-flood years. However, columns (2)-(5) show that there is much less evidence for insurance take-up after a flood using any of the other geographic neighbor definitions. The point estimates are only about one-third as large as those for the media neighbors in Panel A. Just 6 of the 24 flood coefficients that track take-up to 5 years after a flood are statistically significant. None of these are significant at the 1% level. An F-test of equality between each of the 6 statistically significant geographic take-up coefficients and the media market coefficients for the same time lag can be rejected in 4 of the 6 instances.[7]

Appendix Table 10 shows the estimated coefficients from a model that isolates neigh-

[7]The p-values are 0.11 and 0.25 for the two cases where the Null Hypothesis of equality can't be rejected.

boring communities that are only media market neighbors (Panel A) or only geographic neighbors (Panel B). The estimating model is identical to the model for Appendix Table 9 except that the model now includes media market by geography event time indicators (not shown in the table). These indicators are identified off of those communities that are both a geographic neighbor and in the same media market.[8] Thus, the media market estimates in Panel A are those communities in the same media market, but geographically farthest from the flood. The geographic neighbor estimates in Panel B are for communities relatively close to the flood, but which receive their local TV news from a non-flooded media market.

The media market neighbor take-up coefficients in Panel A of Appendix Table 10 are consistent across all 5 columns and do not depend on the definition of a geographic neighbor. The media coefficients are also very similar to those in both Appendix Tables 8 and 9. In Panel B the economically largest point estimates are in column (1). These communities are the very closest communities in non-flooded counties. Take-up in the 5 years after a flood range from 1.2% to 4.6%, or at most, about half as large as communities in flooded counties. Most of the take-up coefficients for the geographic neighbors in columns (2)-(5) are economically small and not statistically significant or only marginally significant, with the notable exception of communities among the closest 20 counties. The point estimates for communities in the closest 20 counties are statistically significant at the 5% level for the first 5 years after a flood. However, the point estimates are only about one-third to one-half as large as the media neighbor point estimates in column (4) and an F-test for equality can be rejected for each lagged pair of coefficients. The point estimates for the geographic neighbor coefficients are very similar across columns (2)-(4). One potential reason for the greater statistical significance for the geographic neighbor coefficients in column (4) of Appendix Table, relative to columns (2) and (3), is that the regression simply has more power due to the larger geographic area.

Varying Geographic ("Ring") Distance

Appendix Tables 11 - 13 consider a 2nd type of geographic neighbor definition that examines "rings" around PDD flooded counties. Rather than considering communities in the 1,5,10, and 20 closest non-flooded counties, the neighbor "ring" regressions consider the closest 1, 2-5, 6-10, and 11-20 non-flooded counties. Appendix Tables 11 - 13 repeat the exact same empirical specifications as in Appendix Tables 8 - 10 except that the "ring" definition of neighbors replaces the accumulative definition. The closest 1 and adjacent county neighbors don't change, but are left in the 2nd set of tables to facilitate an easy comparison. Overall the results are very similar and do not depend on the type of geographic neighbor definition. However, a comparison of column (4) of Appendix Table 13 with column (4) of Appendix Table 10 shows that the statistical significance of the geographic neighbors largely disappears when considering communities in the closest 11-20 counties rather than the closest 20 counties. The point estimates are small and of a similar magnitude between the two specifications. The statistical significance in column (4) of Appendix Table 10 appears to be due to the larger sample size.

[8] The media market by geography indicators are negative, occasionally statistically significant, and range from 1%-3% for the first 5 years after a flood.

E.9 Crowding Out of TV Flood News Stories

I investigate whether the reporting of floods on local TV news broadcasts is crowded out by other important national news stories. The estimation strategy is to compare the number of flood stories in months when there is a PDD flood and no important national news story, with the number of PDD flood stories in months when there is a PDD flood and an important national news story. I run a panel regression using a media market by month panel for the years 2003-2007 (60 months). The dependent variable is the number of flood news stories per station in a TV media market in a particular month. The independent variables include: an indicator for whether there is a PDD flood in the media market, an indicator for whether there is an important national news story, and an interaction term that equals one if there is both a flood and an important national news story. The coefficient of interest is from the interaction term. The Null Hypothesis of crowing out predicts a negative coefficient on the interaction term. The panel uses a balanced panel of media markets. Refer to Appendix Sections D.3 and D.5 for details on the media market and news story data.

We created the list of the 3-5 largest national TV news events for each year from 2003-2007. The starting point for creating the list is the Wikipedia page for each calendar year (for 2003, `http://en.wikipedia.org/wiki/2003`). The events on this page are then cross-referenced with the yearly event list published by CNN (for example, `http://www.cnn.com/SPECIALS/2003/yir/`). The rationale for selecting 3-5 events is based on the estimation strategy. We want to label fewer than half of the months each year as including a national news story. There is admittedly some discretion involved in selecting the list. We had hoped to use a pre-existing list derived from market research on the most covered TV news stories and published by an organization that studies the news media. To our surprise, we were not able to locate such a list. We estimate the "crowding out" effect using different subsets of national media events as a means to help reduce bias in selecting the list of media events. Failure to correctly identify the most covered national TV media events is likely to bias coefficient estimates on the interaction term towards zero.

Table 14 lists the important national news events, the date of the event, and whether the event is part of the sports, politics, or disaster sublist. Table 15 presents the regression results of the flood news story crowding out analysis. There are 4 panels in the table. Each panel corresponds to a different group of news events. The three columns show estimates using three different regression specifications. Column (1) doesn't include any control variables. Column (2) adds media market fixed effects. Column (3) adds month fixed effects. Standard errors are clustered by media market in each specification. The point estimate for the interaction term is always negative and is statistically significant in about half of the specifications. Overall there is modest support for the hypothesis that important national news events crowd out reporting of large local floods.

F Comparison of Learning Models

This section provides more details on the learning model comparison and conditional probability simulation discussed in section 5 of the manuscript. I use learning model Equation

(4) to simulate probability time series given different values of the weighting parameter δ. The first step in simulating the flood probabilities is to set the starting values for α and β in Equation (4). I consider three different methods for setting the starting values, each of which implies a different assumption over homeowner knowledge: (i) Use the National Flood Distribution, (ii) Use the State Flood Distribution, (iii) Use each County-Specific Flood History.

There are two advantages in using either the national or state flood distributions to set initial flood expectations. Using the national or state distributions allows one to precisely pin down the two fixed parameters in the learning model by matching the first two moments of the empirical flood distribution with the first two moments of the Beta Distribution (Davis [2004]). In this way, the initial beliefs are set using a straightforward moment matching procedure that is closely linked to the historical flood distribution, and has a clear economic interpretation. The state distribution approach says that residents in Florida, for example, know that they are in a high flood risk state, but that they are still learning about their county's flood risk relative to other Florida counties. The second advantage is that most Bernoulli Bayesian models use the Beta Distribution as a prior distribution because it is a conjugate prior and has nice statistical properties (DeGroot [1970]). PDD county-level flooding in the US from 1958-2007 closely fits the Beta Distribution (Appendix Figure 4). Thus, the Beta Distribution actually offers a good empirical fit for the national historical flood distribution. This is also true for most of the US State distributions.

The disadvantage of using either the national or state flood distributions is that it assumes that homeowners have a very imprecise prior. As it turns out, the simulated flood probabilities using such an imprecise prior do a poor job of matching observed take-up regardless of the value of the weighting parameter.

Using only historical flooding in each county to set initial beliefs has the advantage that homeowners in each county have county-specific starting values. The practical challenge of this approach is that there is not an obvious way to empirically pin down both parameters in the learning model. The approach the paper takes is to assume that the homeowner begins with the "correct" expectation, but that confidence in this belief (uncertainty of the prior) can vary. We set the first moment of the Beta Distribution ($E[p] = \frac{\alpha}{\alpha+\beta}$) equal to the mean yearly probability of a flood for each county for the years 1958-2007. The assumption is that these 50 years approximate the true underlying flood probability for each county. We then consider α, β combinations that fit this equation, by varying $\alpha \in (0, 15]$. No model simulation with an $\alpha > 10$ provides a statistical fit for the observed pattern of insurance take-up. We discretize the α parameter space by 0.1 units. By construction, a smaller α implies a smaller β. Together, α and β close to zero imply a highly uncertain prior belief. When α and β are small, the initial beliefs are "weak" and homeowners will almost ignore their initial beliefs when updating expectations.

Regardless of the approach to set initial beliefs, as the number of yearly observations increases, the weight of the prior in determining the revised conditional expectation becomes smaller. The intuitive reason for this is that the information content of the initial parameter values become less important as the overall stock of information increases. We simulate conditional flood expectations beginning in 1958. Thus, there is a 22 year "burn in" period before the beginning of the event study panel in 1980.

Note that there are slightly fewer communities in the estimating panel as compared to

Figure 4 in the text. The reason is that I drop communities in counties that don't have a pdd flood from 1958-2007 (rather than assign them a zero flood probability). The number of communities is reduced by 82 from 9,607 to 9,525.

We select the time series of flood probabilities, $p(\delta)_{ct}$, that minimizes the mean square error of $ln(takeup_{ct}) = \alpha + \beta_t lnp(\delta)_{ct} + \alpha_c + \gamma_{st} + \epsilon_{ct}$ This equation is the same as the primary event study estimating equation, except that here we replace the event time dummy variables with log flood probability. As a practical matter, we use a 2-step process. First, we run the baseline event study equation with both log insurance take-up and log simulated probability as dependent variables. Note that there are 3,900 distinct probability time series for the simulations that use county-specific starting values (150 alpha/beta combinations for 26 different weighting parameter specifications).

Second, we use a minimum distance estimator (Abowd and Card [1989]; Chamberlain [1982]; Farber and Gibbons [1996]) to gauge the learning model fit. The minimum distance estimator can be written as: $(\hat{q}_\tau - p_\tau)'V^{-1}(\hat{q}_\tau - p_\tau)$, where p_τ is the simulated event time probability for τ years after a flood using Equation (1) from the text, with $lnp(\delta)_{ct}$ as the dependent variable, $\hat{q}_\tau$ is the coefficient estimate from the flood insurance event study and V^{-1} is the inverse variance matrix for the take-up coefficients. The variance matrix has the effect of weighting the difference between the coefficient estimates for each event moment based on the precision of the estimated take-up coefficient. The estimator is (asymptotically) distributed χ^2 with 28 degrees of freedom. Three parameters (α, β, δ) are estimated using the 15 estimated pre-flood coefficients and the 16 post-flood coefficients. The take-up coefficients for the year before a flood and the year of a flood are not used in calculating the goodness-of-fit statistic. Take-up the year before a flood is normalized to zero. We do not use the coefficient from the year of a flood because of the possibility that there is a mechanical delay in the recorded purchase of flood insurance. Nevertheless, results that do consider the year of a flood are very similar.

The fit of each model is determined by observing how well the changes in simulated probabilities match the changes in insurance take-up in the years preceding and following a flood. It is important to remember that the event study framework controls for the different flooding histories for each community, while focusing attention on how conditional flood probabilities change after a new flood under each assumed learning model. Intuitively, the estimator gives an indication of how well the complete insurance take-up impulse response function matches the conditional probability impulse response function.

Figure 5 graphs insurance take-up (circles) and flood probability coefficients (squares and triangles) from the estimation of Equation (1) using the 1980-2007 flood event study panel. The same regression is run three times, once for each dependent variable. The triangles are conditional probabilities from the best-fitting model ($\delta = 0.91$), while the squares are conditional probabilities from the Full Information model ($\delta = 1$). Each probability uses the same starting values with $\alpha = 6.2$. Insurance take-up has the exact same pattern and very similar magnitudes as in Figure 4 of the manuscript (i.e. the event study is robust to reducing the sample by 82 counties). Standard error bars have been omitted to better facilitate a comparison between the coefficients.

The pre-period change in conditional probabilities for the Discounting Model are all precisely estimated zeros, which matches the (statistical) zeros for changes in insurance take-up. The implied post-flood slope in insurance take-up is very similar to that of the simulated probabilities from the Discounting Model. The notable exception is in the year of a flood. By way of comparison, the Full Information conditional probabilities imply a much flatter slope in the post-flood impulse response function. This stylized fact is common across the vast majority of starting value parameterizations of the learning model that compare a model with the best-fitting parameter (which implies $\delta < 1$) and the Full Information Model ($\delta = 1$).

The second type of incomplete information Bayesian model I consider is one where homeowners only use historical flood information which they observe first-hand. I still allow for the information that is used to be discounted by the weighting parameter δ. One example is if new homeowners who move to a community don't consider any historical information before their arrival.

I calibrate this 2nd incomplete information model using national county migration flows. I use IRS county migration data and calculate the average migration rate (across both counties and years) from 1980-2007 to be 5.5%. I then use this migration rate to create a cohort-based migration profile for the "typical" community. The assumption used in creating this profile is that the migration rate is independent of the number of years of residence in the community. The calibration is meant as a benchmark and not to accurately account for exact migration differences over time or between counties. A learning model without discounting, but where homeowners still have incomplete information due to migration can match the spike and decay pattern of flood insurance take-up.

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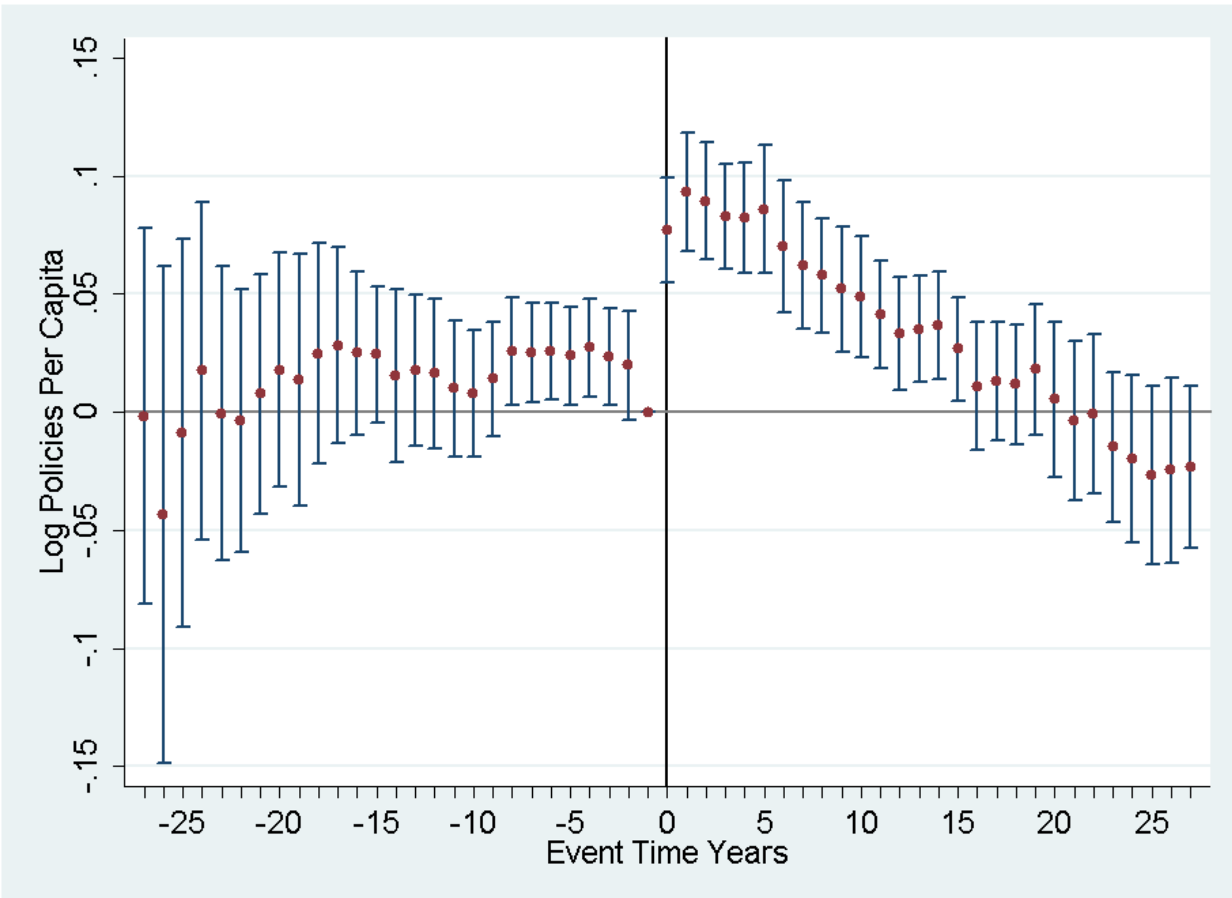
H Appendix Figures and Tables

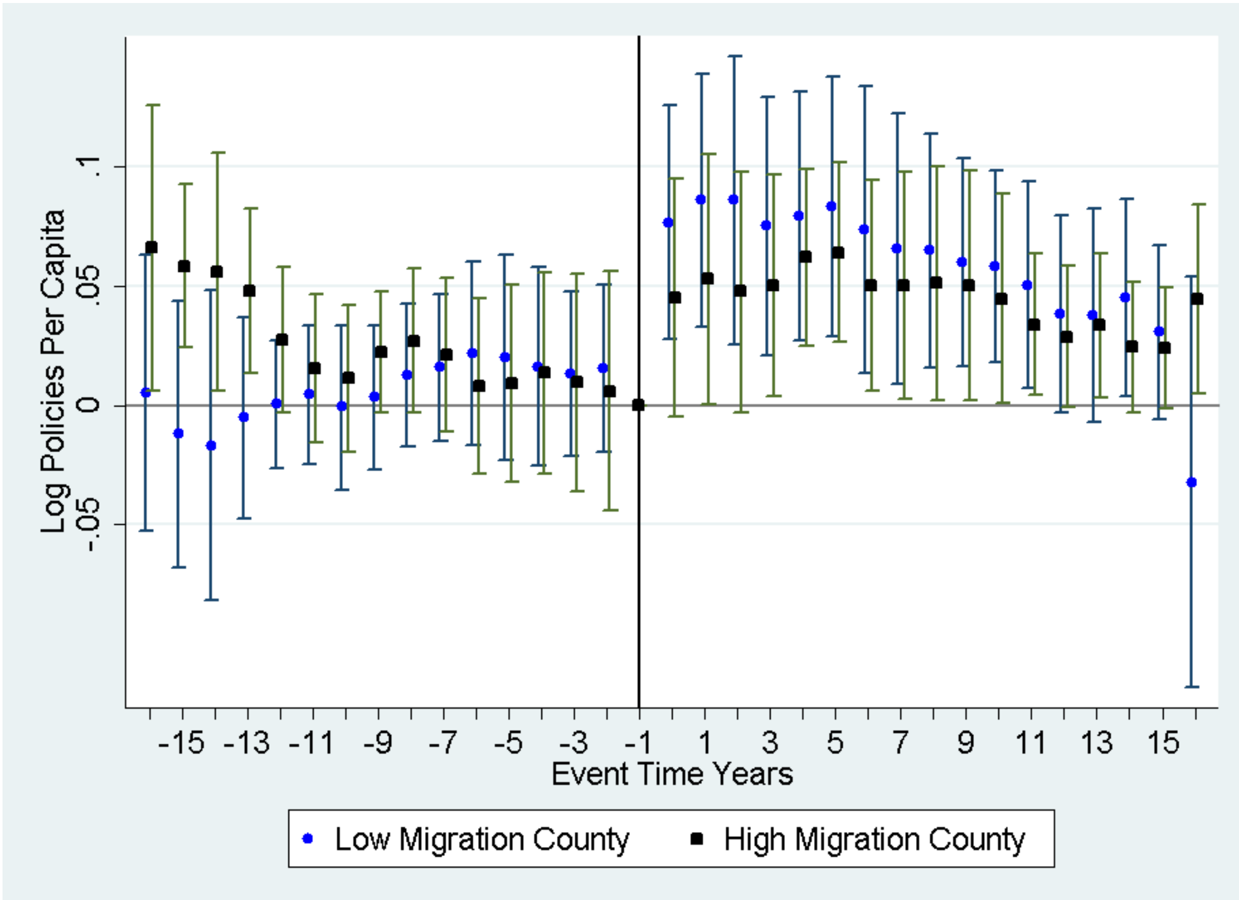
H.1 Figures

Figure 1: Community Flood Insurance Take-up 1980-2007 Panel



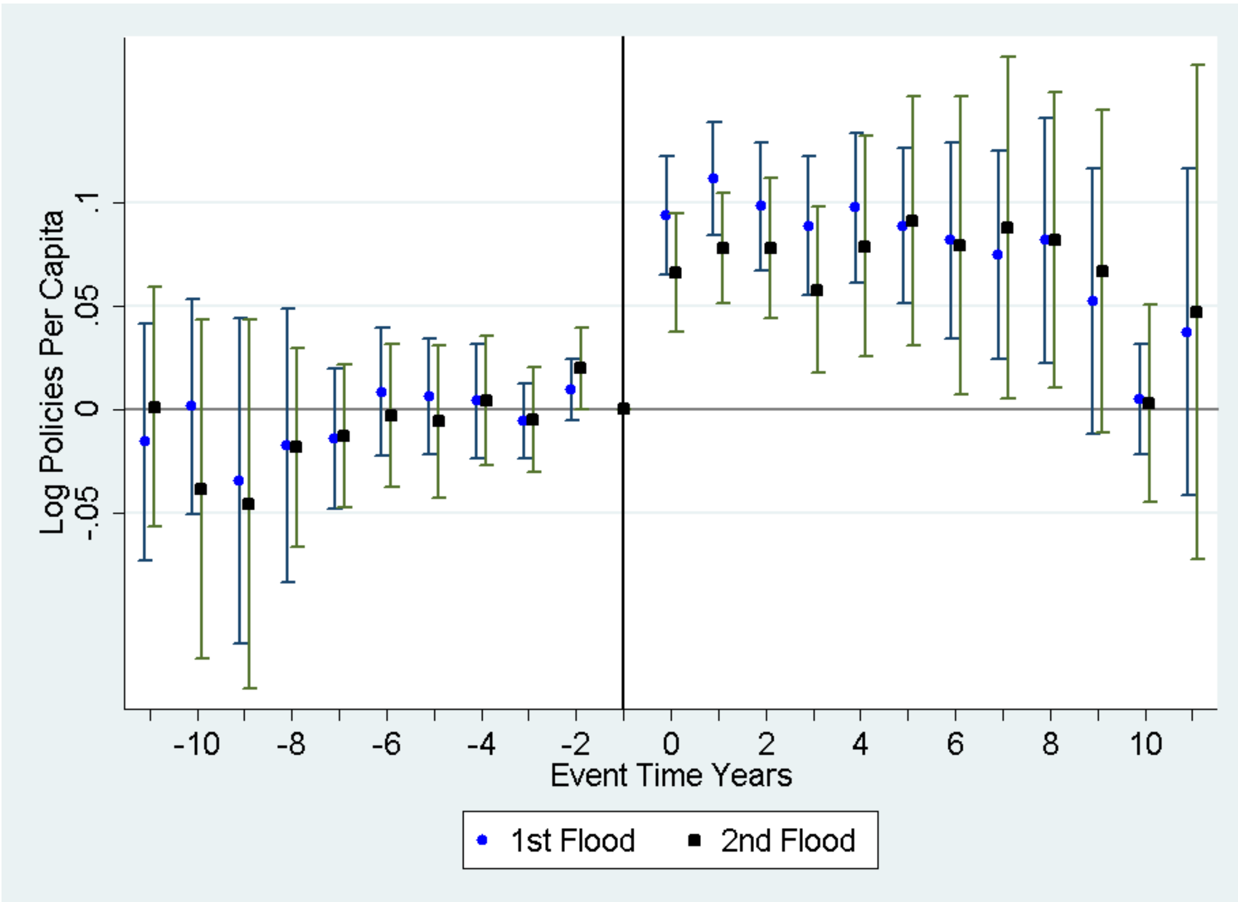
This figure shows insurance take-up point estimates from the same specification as Figure 4 in the text, except that the end points of the event study are not binned. The figure plots event study coefficients from the estimation of Equation (1) using the 1980-2007 panel. The designation of a flood is whether the community is located in a Presidential Disaster Declaration County. Refer to Section 3 of the text and the notes to Figure 4 for more details.

Figure 2: Flood Insurance Take-up after a Flood for Homeowners in Low and High Migration Counties, 1984-2007 Panel



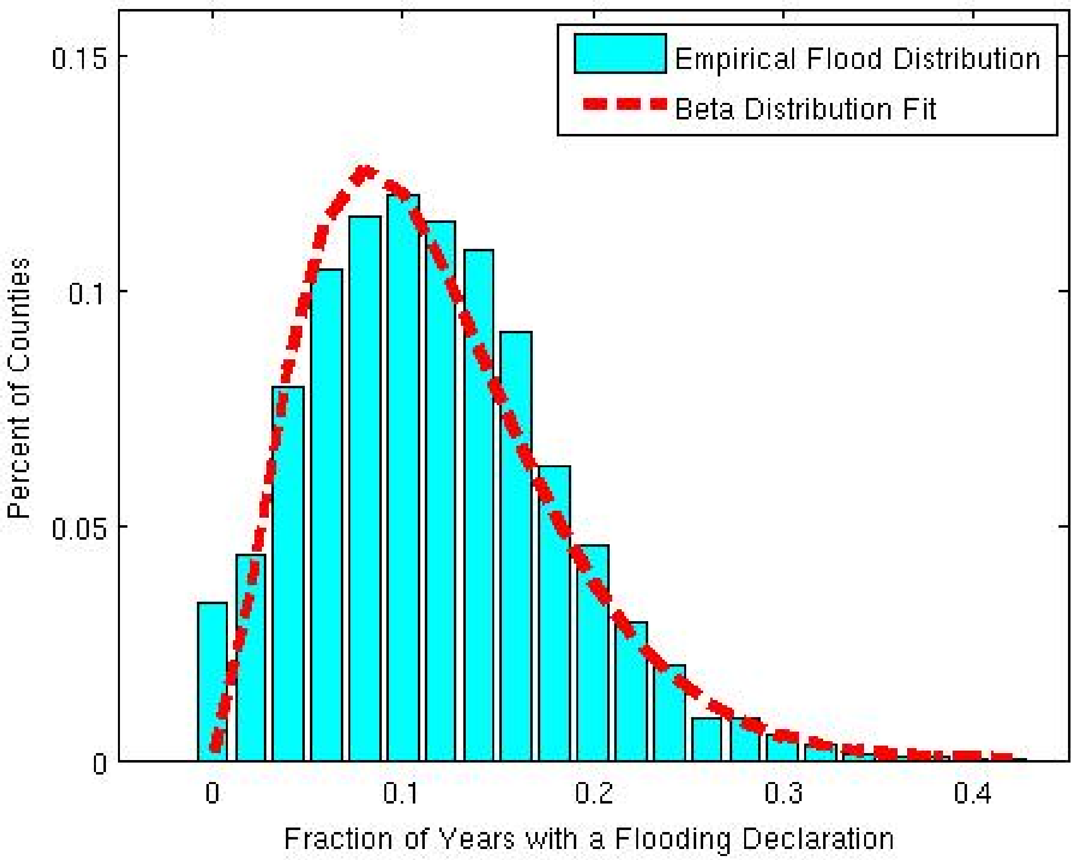
The figure plots event time insurance take-up coefficients from the estimation of a version of Equation (1) that separately measures the effect on homeowners living in low (circles) and high (squares) migration counties. The bars show the 95% confidence intervals. There are two differences between this specification and the baseline estimation of Equation (1) using the 1980-2007 Panel shown in Figure 4 of the text. First, two sets of event time indicators are included in the specification to separately measure the effect for homeowners in above and below migration counties. A low (high) migration county is one that is below (above) median among all counties in our sample based on the average county migration rate from 1984-2007. Two sets of event time indicators are included in the specification to separately measure the effect for homeowners in above and below migration counties. Second, county migration data are only continuously available for the years 1984-2007, so the panel is restricted to the years 1984-2007.

Figure 3: Flood Insurance Take-up after 1st and 2nd Flood Hits, 1990-2007 Panel



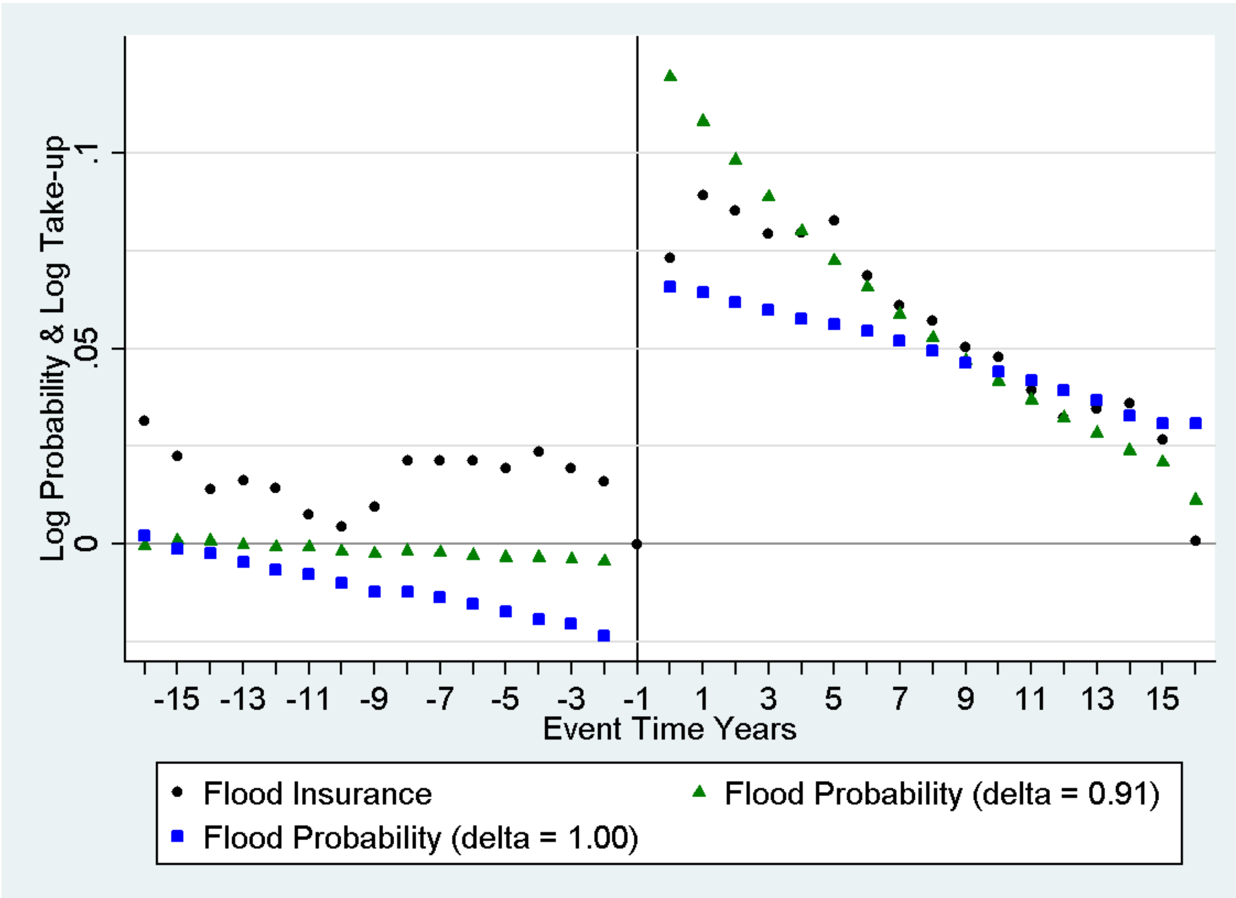
This figure plots event time insurance take-up coefficients from the estimation of a version of Equation (1) that separately measures the effect of 1st (circles) and 2nd (squares) flood hits using the 1990-2007 Panel. The bars show the 95% confidence intervals. The baseline estimation of Equation (1), shown in Figure 2 of the text, provides the average effect across all floods. There are 10,841 communities in the panel. 6,914 communities are hit by at least one flood and 3,822 by at least two floods. Refer to Section 3 of the text and the notes to Figure 4 for more details.

Figure 4: Distribution of US Counties by Likelihood of a Presidential Disaster Declaration Flood from 1958-2007



The figure graphs the yearly probability of a Presidential Disaster Declaration (PDD) Flood in each US county for the 50 years between 1958-2007. The histogram includes data from all 2704 counties in the 1980-2007 panel. The horizontal axis measures the fraction of years with a PDD flood and is calculated for each county by dividing the number of years with at least one PDD flood by 50. Each vertical bar shows the percent of counties with each 50 year flooding probability. The dashed curve is for a Beta Distribution with parameter values alpha = 2.87 and beta = 21.87. The parameter values are selected by matching the first two moments of the Beta Distribution to the first two moments of the empirical flood distribution shown in the histogram.

Figure 5: Flood Insurance Take-up and Simulated Probabilities



This figure plots the event study coefficients from three separate regressions using manuscript Equation (1) and the 1980-2007 panel. The three regressions differ only by the dependent variable: log insurance take-up (circles), and log simulated probability from the Full Information (squares) and Discounted (triangles) Bayesian model. The conditional probabilities are from a model that sets the initial values (prior beliefs) equal to the true expectation using historical flooding in the county and a value for $\alpha = 6.2$. Refer to Appendix Section F and Section 5 of the manuscript for more details.

H.2 Tables

Table 1: (Online Appendix) Mandatory Purchase Enforcement Calculation

Data from GAO [1992]

No. eligible SFHA properties: 843
No. eligible SFHA properties required to have insurance: 190 (22.5%)
No. eligible SFHA properties required to have insurance that have insurance: 123 (64.7%)

Approx. 46% of homeowners required to purchase insurance would purchase anyway

Best estimate (Dixon et al. [2006]) is 50% of single family homes in SFHA have flood insurance
Use this estimate to calculate no. of properties that didn't require insurance that had insurance:

$$\text{(\% required)*(\% w. insurance)} + \text{(\% not required)*(\% w/ insurance)} = 0.50$$

$$0.225 * 0.647 + 0.774 * X = 0.50$$

$$X = 0.457 \text{ or } \boxed{45.7\%}$$

Insurance purchase model is applicable to approx. 96% of the households in the SFHA

Estimating the % of SFHA homeowners who purchased insurance but otherwise would not have:

$$\text{(No. required w/ insurance) - (No. required that would choose to purchase)}$$

$$123 - (190 * 0.457) = 36.2$$

% of homeowners in SFHA who purchased insurance because they were compelled to:

$$36.2/843 = 0.43 \text{ or } \boxed{4.3\%}$$

Insurance purchase model is applicable to approx. 97% of the households with insurance

According to Dixon et al. [2006], $\approx \frac{1}{3}$ of the policies-in-force are for households outside the SFHA
% of homeowners (both in and outside of SFHA) who purchased insurance b/c they were compelled to:

$$0.043 * (2/3) + 0.0 * (1/3) = 0.029 \text{ or } \boxed{2.9\%}$$

Insurance purchase model is applicable to $\approx$ 99% of households in 500-year floodplain

According to Dixon et al. [2006] 99% of households live outside SFHA
Approx. 96% of land is outside SFHA, but inside 500-year floodplain (see Appendix Table 3):

$$0.87/(0.87 + 0.04) = 0.96 \text{ or } 96\%$$

Approx. 95% of households are outside SFHA, but inside 500-year floodplain:

$$0.96 * 0.99 = 0.95 \text{ or } 95\%$$

Percent of households in 500-year floodplain not effected by requirement:

$$0.97 * (0.01/(0.01 + 0.95)) + 1 * (0.95/(0.01 + 0.95)) = 0.999 \text{ or } \boxed{99\%}$$

This table uses survey evidence from GAO [1992] and estimates from Dixon et al. [2006] to examine the 1973 NFIP Amendment that stipulates that homeowners with federally insured mortgages whose residences are in Special Flood Hazard Areas (i.e. the 100-year flood plain) are required to maintain flood insurance. A number of government sponsored and academic studies have concluded that this mandatory purchase amendment is not widely enforced. This table outlines a simple calculation using existing estimates which shows that only about 3% of households purchase insurance because they are compelled to do so by the mandatory purchase provision. Thus, the paper's insurance purchase model is applicable to 97% of the households with flood insurance policies. The model also describes the purchasing decision faced by more than 99% of potential buyers residing within the 500-year flood plain. Refer to Online Appendix Section B.3 for more details.

Table 2: (Online Appendix) Yearly Insurance Premium Rate Change

	(1)	(2)
	Actuarial Rate Properties	Grandfathered Properties
Panel A: Yearly Insurance Premium Rate Change (Percent Real Dollars)		
1996	-0.9	6.7
1997	4.9	10.1
1998	3.2	-0.4
1999	0.5	-1.3
2000	0.8	-1.4
2001	0.4	-0.1
2002	1.3	0.7
2003	-0.4	1.3
2004	-2.6	2.4
2005	-1.1	-3.1
Panel B: Ten Year Insurance Premium Summary Statistics		
Avg. Yearly Percent Increase	0.61	1.49
No. Years Premium Increase	6	5
No. Years Premium Decrease	4	5

Columns (1) and (2) show the change in the annual insurance premium for actuarial rate-based and grandfathered properties. Panel A provides the annual rate change for the 10-year period from 1996-2005. The nominal NFIP rate adjustments are converted to real rates of change using the Consumer Price Index (CPI) for each year. The yearly premium adjustments are not available separately for the last two years of the insurance panel (2006 and 2007) or before 1996. The NFIP does provide an estimate of the average nominal percent rate increase across the two classes of properties for the last two years, which after adjusting for inflation, are: 2006 (0.9%) and 2007 (3.2%). Panel B provides summary statistics over the 10 year period. The CPI table used for inflation adjustments can be found here: `ftp://ftp.bls.gov/pub/special.requests/cpi/cpiai.txt`. The NFIP yearly premium adjustments are documented in the Actuarial Rate Review documents here: `http://www.fema.gov/business/nfip/actuarial\_rate.shtm`. The NFIP provided spreadsheets of the rate increases (available on request) for the years 1996-2000.

Table 3: (Online Appendix) Testing the Hypothesis that Floods are Independent for Two Floods using Event Windows of 5 to 10 Years

	(1)	(2)	(3)	(4)	(5)	(6)
Window Size	5 yrs	6 yrs	7 yrs	8 yrs	9 yrs	10 yrs
Chi Square Test Statistic	17.92	0.04	0.81	8.61	16.80	4.81
Total Sequences	2546	2262	2041	1887	1722	1598
Expected Consecutive Floods	636.5	452.4	340.2	269.6	215.3	177.6
Observed Consecutive Floods	729	456	325	225	159	150
Reject Null of I.I.D. Floods	X			X	X	X
More Consecutive Floods Than Expected	X					
Fewer Consecutive Floods Than Expected				X	X	X

This table provides an additional test for the hypothesis that annual Presidential Disaster Declaration (PDD) floods are independently and identically distributed. Columns (1) through (6) correspond to flood event year windows of sizes 5 to 10 years. Each sequence of years contain exactly two PDD floods, including a flood in the first year. Each column tests the hypothesis of independence using a Chi-Square test with one degree of freedom. The test considers the expected probability of having the 2nd flood event in the 2nd year of the sequence (consecutive flood years) verses <u>not</u> having the 2nd flood in the 2nd year. Some counties contribute multiple flood year sequences in each of the event year window sizes. The critical cutoff values for rejection of the null hypothesis are 2.71 (10% level), 3.84 (5% level), and 6.63 (1% level). The null hypothesis is rejected in 4 of the 6 samples at the 5% level. In three of the samples there is evidence that a flood is less likely to occur in the year following a flood. One of the samples suggests that a flood is more likely to occur. Overall the table provides mixed evidence in support of the maintained hypothesis of independence, and no clear evidence that a flood is more likely to occur in a year following a flood.

Table 4: (Online Appendix) Community Flood Insurance Statistics and Flood Map Characteristics

Panel A: Flood Map Designation	**100 Yr**	**100-500 Yr**	**Outside Flood Plain**
% Communities by Flood Designation			
Percent of Community	14 (8)	77 (87)	4 (0)

Panel B: Year	**1980**	**1990**	**2007**
Community Policies Per 1,000 Persons			
< Median 100 Year Flood Plain	6 (1)	4 (1)	8(2)
> Median 100 Year Flood Plain	40 (3)	44 (3)	62 (7)

Community flood map designations are calculated from electronic Corps of Engineer (FIRM) flood maps using GIS software that calculates the land area of each community within each flood designation. The electronic flood maps were provided by FEMA for all communities with an electronic copy of the flood map as of May 2009. The statistics are calculated for the 25% of the 1980-2007 panel of communities (2,398) for which electronic maps are available. Panels A and B list summary statistics for community mean and median (in parenthesis). Refer to Section 2 of the text and Appendix Section D for details on flood insurance and flood map data.

Table 5: (Online Appendix) Event Time Estimation for Panel 1990-2007 Specification Checks

	(1)	(2)	(3)	(4)	(5)	(6)
Specification:	Flooded Cnties Only	NFIP by 1980	Norm. to 11+ Years	Dep Var In Levels	D-K SEs	Exclude Louisiana
Panel A: Years Before a Community is Flooded						
11-17 Yrs Before Flood	-0.012 (0.014)	-0.008 (0.014)		-0.002 (0.003)	-0.011 (0.011)	-0.010 (0.014)
10 Yrs Before Flood	-0.008 (0.016)	-0.007 (0.017)	0.000 (0.013)	-0.001 (0.001)	-0.007 (0.021)	-0.006 (0.016)
9 Yrs Before Flood	-0.015 (0.026)	-0.016 (0.028)	-0.007 (0.023)	-0.002 (0.002)	-0.014 (0.029)	-0.015 (0.027)
8 Yrs Before Flood	0.001 (0.015)	-0.001 (0.016)	0.010 (0.014)	-0.002 (0.002)	0.002 (0.016)	0.004 (0.015)
7 Yrs Before Flood	0.004 (0.011)	0.001 (0.010)	0.012 (0.015)	-0.001 (0.001)	0.004 (0.011)	0.006 (0.011)
6 Yrs Before Flood	0.014 (0.013)	0.011 (0.012)	0.022 (0.017)	-0.001 (0.001)	0.014 (0.006)	0.015 (0.013)
5 Yrs Before Flood	0.009 (0.013)	0.009 (0.013)	0.018 (0.018)	0.000 (0.001)	0.010 (0.009)	0.013 (0.013)
4 Yrs Before Flood	0.013 (0.014)	0.012 (0.014)	0.021 (0.019)	0.006 (0.004)	0.013 (0.010)	0.016 (0.015)
3 Yrs Before Flood	0.003 (0.013)	0.003 (0.013)	0.011 (0.018)	0.001 (0.001)	0.003 (0.008)	0.005 (0.013)
2 Yrs Before Flood	0.015 (0.010)	0.015 (0.010)	0.023 (0.016)	0.001 (0.001)	0.016 (0.009)	0.016 (0.010)
1 Yr Before Flood			0.010 (0.015)			
Panel B: Years After a Community is Flooded						
Year of Flood	0.078 (0.010)***	0.076 (0.010)***	0.086 (0.014)***	0.003 (0.001)**	0.078 (0.022)***	0.079 (0.010)***
1 Yr After Flood	0.091 (0.008)***	0.089 (0.008)***	0.099 (0.012)***	0.007 (0.003)**	0.092 (0.016)***	0.092 (0.008)***
2 Yrs After Flood	0.084 (0.010)***	0.083 (0.011)***	0.092 (0.014)***	0.004 (0.002)***	0.085 (0.011)***	0.083 (0.010)***
3 Yrs After Flood	0.071 (0.011)***	0.069 (0.011)***	0.079 (0.015)***	0.003 (0.001)***	0.072 (0.011)***	0.071 (0.012)***
4 Yrs After Flood	0.077 (0.012)***	0.075 (0.012)***	0.085 (0.016)***	0.003 (0.001)***	0.077 (0.013)***	0.075 (0.012)***
5 Yrs After Flood	0.073 (0.012)***	0.071 (0.012)***	0.081 (0.016)***	0.003 (0.001)***	0.073 (0.012)***	0.070 (0.012)***
6 Yrs After Flood	0.065 (0.012)***	0.061 (0.012)***	0.073 (0.015)***	0.003 (0.001)***	0.065 (0.013)***	0.063 (0.012)***
7 Yrs After Flood	0.061 (0.013)***	0.059 (0.013)***	0.068 (0.014)***	0.003 (0.001)**	0.060 (0.015)***	0.060 (0.013)***
8 Yrs After Flood	0.063 (0.016)***	0.062 (0.016)***	0.071 (0.016)***	0.003 (0.001)**	0.063 (0.018)***	0.063 (0.016)***
9 Yrs After Flood	0.035 (0.016)**	0.034 (0.017)**	0.042 (0.018)**	0.003 (0.002)	0.035 (0.014)**	0.035 (0.017)**
10 Yrs After Flood	0.024 (0.016)	0.025 (0.017)	0.032 (0.018)*	0.001 (0.001)	0.024 (0.013)*	0.024 (0.017)
11-17 Yrs After Flood	0.017 (0.020)	0.017 (0.019)	0.024 (0.023)	0.000 (0.001)	0.016 (0.014)	0.017 (0.021)
Community FE	X	X	X	X	X	X
State-by-Year FE	X	X	X	X	X	X
Observations	184,662	184,518	195,138	195,138	195,138	191,412
Communities	10,259	10,251	10,841	10,841	10,841	10,634
R^2	.2237	.2183	.2180	.0157	.2180	.2165

Each column contains coefficients from a distinct regression of a version of Equation (1). Column (1) drops communities in counties that don't have a flood during the panel. Column (2) drops communities if flood insurance is not available beginning 10 years before the panel period. Column (3) normalizes the event study to the beginning of event time. Column (4) uses insurance take-up levels as the dependent variable (number of insurance polices per capita). Column (5) considers how the precision of the estimates change when allowing for a general form of spatial correlation as proposed by Driscoll and Kraay [1998]. Column (6) excludes all communities in Louisiana from the sample. Refer to Appendix Section E.1 for more details.

Table 6: (Online Appendix) Flood Insurance Take-up Balanced Event Time Windows of 11 and 21 Years

	(1)		(2)		(3)		(4)	
Specification:	Hit 5 Yr Window		Hit 10 Yr Window		PDD 5 Yr Window		PDD 10 Yr Window	
Panel A: Years Before a Community is Flooded								
10 Yrs Before Flood			0.039	(0.057)			0.006	(0.027)
9 Yrs Before Flood			0.059	(0.053)			0.007	(0.025)
8 Yrs Before Flood			0.061	(0.050)			0.034	(0.026)
7 Yrs Before Flood			0.039	(0.045)			0.022	(0.025)
6 Yrs Before Flood			0.054	(0.040)			0.017	(0.023)
5 Yrs Before Flood	-0.007	(0.029)	0.036	(0.035)	0.009	(0.011)	0.024	(0.022)
4 Yrs Before Flood	0.002	(0.024)	0.044	(0.036)	0.013	(0.012)	0.027	(0.025)
3 Yrs Before Flood	-0.018	(0.018)	0.042	(0.031)	0.006	(0.012)	0.020	(0.026)
2 Yrs Before Flood	-0.015	(0.010)	0.028	(0.025)	0.002	(0.011)	0.016	(0.026)
Panel B: Years After a Community is Flooded								
Year of Flood	0.110	(0.021)***	0.226	(0.043)***	0.082	(0.020)***	0.183	(0.046)***
1 Yr After Flood	0.081	(0.037)**	0.176	(0.044)***	0.091	(0.019)***	0.158	(0.039)***
2 Yrs After Flood	0.126	(0.045)***	0.182	(0.051)***	0.082	(0.020)***	0.139	(0.039)***
3 Yrs After Flood	0.091	(0.041)**	0.132	(0.065)**	0.070	(0.019)***	0.108	(0.040)**
4 Yrs After Flood	0.071	(0.032)**	0.080	(0.086)	0.060	(0.017)***	0.082	(0.036)**
5 Yrs After Flood	0.059	(0.035)	0.068	(0.106)	0.049	(0.017)***	0.092	(0.032)***
6 Yrs After Flood			0.059	(0.129)			0.085	(0.035)**
7 Yrs After Flood			0.034	(0.147)			0.059	(0.034)*
8 Yrs After Flood			0.045	(0.165)			0.036	(0.042)
9 Yrs After Flood			0.058	(0.185)			0.039	(0.045)
10 Yrs After Flood			0.030	(0.204)			0.033	(0.038)
Community FE	X		X		X		X	
Year FE	X		X		X		X	
Observations	39,574		19,614		44,077		12,390	
Communities	3,431		934		3,532		590	
R^2	.9481		.9061		.9407		.8898	

Each column contains event time coefficient estimates from a distinct regression of a version of Equation (1), where the panel is balanced in event time. Each specification includes community and calendar year fixed effects. Standard errors are clustered at the state level with significance level: *** 1%, ** 5%, * 10%. Each regression contains many fewer communities and observations as compared to the preferred event study specifications balanced in calendar time (text Figures 2 and 4). The reason for this is that most communities are flooded multiple times. Column (1) considers communities that are hit by a PDD flood and have at least 5 years before and after without a flood hit. Only event time years $\tau \in [-5, 5]$ are included in the event study. 3,195 of the 3,431 communities are hit by one flood, while 235 communities are hit by two floods and one community is hit by three floods (separated by 5+ years). Column (2) considers communities with a least 10 years before and after a flood hit. All 934 communities are hit by exactly one flood and contain 21 observations ($\tau \in [-10, 10]$). Column (3) considers the county-level flood definition. Only event time years $\tau \in [-5, 5]$ are included in the event study. 2,905 of the 3,532 communities are in counties with one PDD flood, while 589 are in counties with two floods and 38 are in counties with three floods (separated by 5+ years). Column (4) again considers county PDD floods. There are 590 communities, each in a county with one PDD flood and 10 years before and after with no PDD floods. All of the communities in column (4) contain 21 observations ($\tau \in [-10, 10]$).

Table 7: (Online Appendix) Flood Insurance Take-up Controlling for Participation in the Community Rating System, Event Study 1996-2007

	(1)		(2)		(3)	
Panel A: Years Before a Community is Located in a PDD-Flooded County						
11-13 Yrs Before Flood	0.020	(0.030)	0.020	(0.030)	0.020	(0.030)
10 Yrs Before Flood	-0.063	(0.032)**	-0.063	(0.032)**	-0.063	(0.032)**
9 Yrs Before Flood	-0.016	(0.022)	-0.016	(0.022)	-0.016	(0.022)
8 Yrs Before Flood	0.010	(0.023)	0.010	(0.023)	0.010	(0.023)
7 Yrs Before Flood	-0.025	(0.014)**	-0.025	(0.014)**	-0.025	(0.014)**
6 Yrs Before Flood	-0.012	(0.013)	-0.012	(0.013)	-0.012	(0.013)
5 Yrs Before Flood	-0.010	(0.010)	-0.010	(0.010)	-0.010	(0.010)
4 Yrs Before Flood	0.016	(0.112)	0.016	(0.112)	0.016	(0.112)
3 Yrs Before Flood	0.012	(0.008)	0.012	(0.008)	0.012	(0.008)
2 Yrs Before Flood	-0.007	(0.007)	-0.007	(0.007)	-0.007	(0.007)
Panel B: Years After a Community is Located in a PDD-Flooded County						
Year of Flood	0.058	(0.016)***	0.058	(0.016)***	0.057	(0.016)***
1 Yr After Flood	0.055	(0.009)***	0.055	(0.009)***	0.055	(0.009)***
2 Yrs After Flood	0.079	(0.018)***	0.079	(0.018)***	0.079	(0.018)***
3 Yrs After Flood	0.058	(0.014)***	0.058	(0.014)***	0.058	(0.014)***
4 Yrs After Flood	0.067	(0.016)***	0.067	(0.016)***	0.067	(0.016)***
5 Yrs After Flood	0.054	(0.018)***	0.054	(0.018)***	0.054	(0.018)***
6 Yrs After Flood	0.041	(0.013)***	0.041	(0.013)***	0.041	(0.013)***
7 Yrs After Flood	0.032	(0.010)***	0.032	(0.010)***	0.032	(0.010)***
8 Yrs After Flood	0.040	(0.009)***	0.040	(0.009)***	0.040	(0.009)***
9 Yrs After Flood	0.028	(0.009)***	0.027	(0.009)***	0.028	(0.009)***
10 Yrs After Flood	0.014	(0.009)	0.014	(0.009)	0.014	(0.009)
11-27 Yrs After Flood	0.042	(0.015)***	0.043	(0.015)***	0.042	(0.015)***
CRS Participation Indicator			0.120	(0.043)***		
CRS Points					0.000	(0.000)
Flood Controls to 1958	X		X		X	
Community FE	X		X		X	
Year FE	X		X		X	
Observations	115,284		115,284		115,284	
Communities	9,607		9,607		9,607	
R^2	.9613		.9613		.9613	

This table considers two event study robustness regressions using the Community Rating System (CRS) data. Column (2) controls for an indicator for CRS community participation (extensive margin). Column (3) includes a variable for the number of points earned (intensive margin). Columns (2) and (3) are otherwise identical to Equation (1) in the paper (the main specification) except that they are run on the 1996-2007 panel with year fixed effects. Column (1) displays the coefficients from the event study regression without either CRS control. Please refer to Appendix Section D for more details on the CRS program and data.

Table 8: (Online Appendix) Flood Insurance Take-up for Communities in Flooded and Neighboring Counties

	(1)		(2)		(3)		(4)		(5)		(6)	
Panel A: Presidential Disaster Declaration County												
Year of Flood	0.065	(0.013)***	0.070	(0.014)***	0.072	(0.014)***	0.079	(0.016)***	0.071	(0.013)***	0.083	(0.014)***
1 Yr After Flood	0.083	(0.014)***	0.089	(0.016)***	0.094	(0.015)***	0.096	(0.015)***	0.089	(0.015)***	0.101	(0.015)***
2 Yrs After Flood	0.078	(0.015)***	0.087	(0.017)***	0.089	(0.016)***	0.090	(0.016)***	0.086	(0.015)***	0.097	(0.015)***
3 Yrs After Flood	0.073	(0.014)***	0.080	(0.016)***	0.083	(0.015)***	0.089	(0.015)***	0.082	(0.014)***	0.093	(0.014)***
4 Yrs After Flood	0.072	(0.014)***	0.077	(0.016)***	0.078	(0.016)***	0.083	(0.015)***	0.080	(0.016)***	0.088	(0.015)***
5 Yrs After Flood	0.074	(0.016)***	0.078	(0.018)***	0.081	(0.017)***	0.085	(0.016)***	0.081	(0.018)***	0.089	(0.017)***
6 Yrs After Flood	0.058	(0.016)***	0.058	(0.017)***	0.058	(0.016)***	0.060	(0.016)***	0.059	(0.017)***	0.065	(0.017)***
7 Yrs After Flood	0.052	(0.015)***	0.051	(0.017)***	0.051	(0.015)***	0.055	(0.016)***	0.049	(0.017)***	0.054	(0.017)***
8 Yrs After Flood	0.049	(0.013)***	0.049	(0.014)***	0.049	(0.013)***	0.053	(0.014)***	0.045	(0.013)***	0.049	(0.015)***
9 Yrs After Flood	0.041	(0.014)***	0.043	(0.015)***	0.044	(0.014)***	0.049	(0.014)***	0.040	(0.014)***	0.046	(0.016)***
10 Yrs After Flood	0.039	(0.013)***	0.040	(0.014)***	0.042	(0.014)***	0.046	(0.015)***	0.037	(0.013)***	0.040	(0.015)***
11-27 Yrs After Flood	0.005	(0.023)	0.005	(0.023)	0.005	(0.024)	0.005	(0.023)	0.003	(0.023)	0.004	(0.022)
Panel B: County Neighboring PDD County and Not Hit by Flood												
Neighbor Def:	Closest 1		Closest 5		Closest 10		Closest 20		Adjacent		Media Market	
Year of Flood	0.024	(0.011)**	0.015	(0.008)*	0.016	(0.006)**	0.021	(0.006)***	0.017	(0.009)*	0.031	(0.006)***
1 Yr After Flood	0.025	(0.011)**	0.020	(0.008)**	0.023	(0.007)***	0.021	(0.006)***	0.018	(0.009)*	0.035	(0.005)***
2 Yrs After Flood	0.026	(0.010)**	0.025	(0.009)***	0.023	(0.008)***	0.019	(0.006)***	0.022	(0.009)**	0.033	(0.006)***
3 Yrs After Flood	0.032	(0.011)***	0.024	(0.010)**	0.023	(0.009)***	0.026	(0.007)***	0.026	(0.010)**	0.036	(0.007)***
4 Yrs After Flood	0.028	(0.011)***	0.016	(0.011)	0.015	(0.009)*	0.019	(0.007)***	0.021	(0.011)*	0.030	(0.007)***
5 Yrs After Flood	0.029	(0.011)***	0.014	(0.011)	0.017	(0.009)**	0.019	(0.007)***	0.018	(0.012)	0.028	(0.009)***
6 Yrs After Flood	0.015	(0.012)	0.001	(0.009)	0.003	(0.008)	0.005	(0.007)	0.005	(0.010)	0.013	(0.007)*
7 Yrs After Flood	0.024	(0.010)**	0.003	(0.012)	0.003	(0.012)	0.008	(0.008)	0.000	(0.012)	0.007	(0.009)
8 Yrs After Flood	0.033	(0.009)***	0.006	(0.010)	0.006	(0.012)	0.012	(0.008)	-0.002	(0.011)	0.006	(0.011)
9 Yrs After Flood	0.029	(0.010)***	0.007	(0.009)	0.008	(0.012)	0.015	(0.007)**	0.001	(0.010)	0.009	(0.009)
10 Yrs After Flood	0.027	(0.011)**	0.003	(0.010)	0.007	(0.011)	0.013	(0.009)	-0.001	(0.009)	0.002	(0.010)
11-27 Yrs After Flood	0.024	(0.018)	-0.014	(0.022)	0.001	(0.017)	0.001	(0.020)	-0.011	(0.015)	-0.042	(0.037)
Pre-Flood Indicators	X		X		X		X		X		X	
Community FE	X		X		X		X		X		X	
State-by-Year FE	X		X		X		X		X		X	
Observations	268,996		268,996		268,996		268,996		268,996		268,996	
Communities	9,607		9,607		9,607		9,607		9,607		9,607	
R^2	.2050		.2051		.2050		.2051		.2051		.2061	

Each column contains coefficients from a distinct regression of Equation (2). All regressions include pre-flood indicator variables for flooded and neighboring communities. The designation of a flood is whether the community is located in a Presidential Disaster Declaration (PDD) County. Each regression uses a different definition of a neighboring community. Columns (1)-(4) consider a neighbor to be a community in the 1,5,10, and 20 geographically closest counties to a PDD county. Column (5) defines a neighbor as a community in a county adjacent to a PDD county. Column (6) defines a neighbor as a community in a county that shares the same TV media market as a a PDD county. Refer to Section 3 of the paper and Appendix Sections D and E.8 for details.

Table 9: (Online Appendix) Flood Insurance Take-up for Communities in Flooded Counties, Geographically Neighboring Counties, and Counties in the Same TV Media Market

	(1)		(2)		(3)		(4)		(5)	
Panel A: Media Market County Neighbor to a PDD Flood County										
Year of Flood	0.030	(0.006)***	0.029	(0.006)***	0.029	(0.006)***	0.026	(0.005)***	0.028	(0.007)***
1 Yr After Flood	0.034	(0.005)***	0.031	(0.004)***	0.030	(0.005)***	0.031	(0.004)***	0.032	(0.005)***
2 Yrs After Flood	0.032	(0.006)***	0.028	(0.005)***	0.028	(0.006)***	0.029	(0.005)***	0.029	(0.006)***
3 Yrs After Flood	0.035	(0.007)***	0.032	(0.007)***	0.032	(0.007)***	0.030	(0.007)***	0.031	(0.007)***
4 Yrs After Flood	0.029	(0.007)***	0.028	(0.007)***	0.028	(0.007)***	0.026	(0.007)***	0.026	(0.007)***
5 Yrs After Flood	0.027	(0.009)***	0.027	(0.008)***	0.026	(0.009)***	0.024	(0.009)***	0.025	(0.008)***
6 Yrs After Flood	0.013	(0.007)*	0.015	(0.007)**	0.015	(0.008)*	0.014	(0.008)*	0.014	(0.007)**
7 Yrs After Flood	0.006	(0.009)	0.008	(0.008)	0.008	(0.008)	0.005	(0.008)	0.009	(0.008)
8 Yrs After Flood	0.005	(0.011)	0.006	(0.010)	0.006	(0.010)	0.002	(0.010)	0.009	(0.010)
9 Yrs After Flood	0.007	(0.009)	0.008	(0.009)	0.007	(0.008)	0.002	(0.009)	0.010	(0.009)
10 Yrs After Flood	0.001	(0.010)	0.001	(0.010)	-0.001	(0.009)	-0.005	(0.010)	0.003	(0.010)
11-27 Yrs After Flood	-0.046	(0.036)	-0.040	(0.032)	-0.050	(0.036)	-0.050	(0.039)	-0.042	(0.037)
Panel B: Geographic County Neighbor to a PDD Flood County										
Neighbor Def:	Closest 1		Closest 5		Closest 10		Closest 20		Adjacent	
Year of Flood	0.016	(0.011)	0.005	(0.008)	0.006	(0.007)	0.013	(0.006)**	0.006	(0.010)
1 Yr After Flood	0.016	(0.011)	0.010	(0.009)	0.013	(0.008)*	0.011	(0.006)**	0.006	(0.010)
2 Yrs After Flood	0.017	(0.010)*	0.016	(0.009)*	0.013	(0.008)	0.010	(0.005)*	0.012	(0.009)
3 Yrs After Flood	0.022	(0.011)*	0.013	(0.011)	0.011	(0.009)	0.016	(0.006)**	0.014	(0.011)
4 Yrs After Flood	0.019	(0.011)*	0.006	(0.011)	0.004	(0.010)	0.009	(0.007)	0.011	(0.012)
5 Yrs After Flood	0.020	(0.011)*	0.003	(0.011)	0.006	(0.009)	0.010	(0.007)	0.007	(0.012)
6 Yrs After Flood	0.010	(0.012)	-0.006	(0.009)	-0.003	(0.008)	-0.002	(0.007)	-0.001	(0.010)
7 Yrs After Flood	0.021	(0.010)**	-0.002	(0.011)	-0.002	(0.012)	0.004	(0.007)	-0.005	(0.012)
8 Yrs After Flood	0.030	(0.010)***	0.001	(0.009)	0.003	(0.012)	0.009	(0.006)	-0.008	(0.011)
9 Yrs After Flood	0.026	(0.010)***	0.003	(0.008)	0.004	(0.012)	0.013	(0.007)**	-0.003	(0.011)
10 Yrs After Flood	0.028	(0.011)**	0.002	(0.009)	0.008	(0.010)	0.015	(0.009)*	-0.001	(0.008)
11-27 Yrs After Flood	0.031	(0.017)*	-0.004	(0.017)	0.020	(0.012)	0.024	(0.019)	0.001	(0.015)
County Flood Indicators	X		X		X		X		X	
Pre-Flood Indicators	X		X		X		X		X	
Community FE	X		X		X		X		X	
State-by-Year FE	X		X		X		X		X	
Observations	268,996		268,996		268,996		268,996		268,996	
Communities	9,607		9,607		9,607		9,607		9,607	
R^2	.2063		.2064		.2063		.2064		.2065	

Each column contains coefficients from a distinct regression of a version of Equation (2). The only difference from the regressions of Appendix Table 8 is that each of the regressions in this table include a set of event time indicator variables for whether a community is in the same TV Media Market (determined by Neilson Research Company) as a flooded community, as well as, a separate set of event time indicators for one of the five geographic neighbor designations. Columns (1)-(4) consider a neighbor to be a community in the 1,5,10, and 20 geographically closest counties to a PDD county. Column (5) defines a neighbor as a community in a county adjacent to a PDD county. Standard errors are corrected for the reduced number of degrees of freedom and clustered at the state level (significance level: *** 1%, ** 5%, * 10%). All regressions include: pre- and post-flood indicator variables, pre-flood indicators for neighboring communities, and state by year fixed effects. Please refer to Section 3 of the paper and Appendix Sections D and E.8 for details.

Table 10: (Online Appendix) Flood Insurance Take-up for Communities in Flooded Counties, Geographically Neighboring Counties not in the same TV Media Market, and Counties in the Same TV Media Market and not in a Geographically Neighboring County

	(1)	(2)	(3)	(4)	(5)
Panel A: Media Market County Neighbor to a PDD Flood County & Not a Geographic Neighbor					
Year of Flood	0.031 (0.006)***	0.033 (0.007)***	0.029 (0.008)***	0.032 (0.010)***	0.036 (0.007)***
1 Yr After Flood	0.034 (0.005)***	0.034 (0.005)***	0.031 (0.006)***	0.031 (0.009)***	0.040 (0.005)***
2 Yrs After Flood	0.033 (0.006)***	0.032 (0.006)***	0.030 (0.007)***	0.031 (0.010)***	0.036 (0.006)***
3 Yrs After Flood	0.036 (0.007)***	0.036 (0.008)***	0.035 (0.009)***	0.035 (0.012)***	0.037 (0.008)***
4 Yrs After Flood	0.030 (0.007)***	0.033 (0.007)***	0.034 (0.008)***	0.031 (0.010)***	0.030 (0.007)***
5 Yrs After Flood	0.028 (0.008)***	0.033 (0.008)***	0.031 (0.009)***	0.033 (0.009)***	0.031 (0.007)***
6 Yrs After Flood	0.013 (0.007)*	0.018 (0.008)**	0.015 (0.008)**	0.014 (0.010)	0.015 (0.007)**
7 Yrs After Flood	0.006 (0.008)	0.010 (0.008)	0.005 (0.008)	0.004 (0.012)	0.007 (0.008)
8 Yrs After Flood	0.005 (0.011)	0.010 (0.011)	0.003 (0.011)	0.009 (0.014)	0.009 (0.011)
9 Yrs After Flood	0.007 (0.009)	0.011 (0.009)	0.008 (0.009)	0.014 (0.012)	0.012 (0.010)
10 Yrs After Flood	0.001 (0.010)	0.004 (0.010)	0.002 (0.010)	0.005 (0.013)	0.007 (0.011)
11-27 Yrs After Flood	-0.047 (0.036)	-0.041 (0.032)	-0.032 (0.030)	-0.063 (0.034)	-0.023 (0.029)
Panel B: Geographic County Neighbor to a PDD Flood County & Not a Media Market Neighbor					
Neighbor Def:	Closest 1	Closest 5	Closest 10	Closest 20	Adjacent
Year of Flood	0.026 (0.024)	0.008 (0.014)	0.006 (0.010)	0.016 (0.007)**	0.020 (0.021)
1 Yr After Flood	0.012 (0.026)	0.014 (0.018)	0.014 (0.009)	0.011 (0.006)*	0.021 (0.021)
2 Yrs After Flood	0.046 (0.027)*	0.028 (0.017)*	0.017 (0.011)	0.011 (0.006)*	0.028 (0.019)
3 Yrs After Flood	0.046 (0.028)*	0.031 (0.018)*	0.017 (0.012)	0.018 (0.007)**	0.028 (0.020)
4 Yrs After Flood	0.036 (0.022)	0.023 (0.018)	0.013 (0.013)	0.012 (0.006)*	0.020 (0.018)
5 Yrs After Flood	0.036 (0.022)	0.026 (0.017)	0.016 (0.014)	0.014 (0.007)**	0.021 (0.017)
6 Yrs After Flood	0.021 (0.026)	0.001 (0.015)	-0.003 (0.013)	-0.002 (0.008)	0.001 (0.014)
7 Yrs After Flood	0.020 (0.030)	0.003 (0.017)	-0.006 (0.018)	0.004 (0.009)	-0.015 (0.018)
8 Yrs After Flood	0.021 (0.028)	0.013 (0.018)	-0.002 (0.018)	0.013 (0.008)	-0.016 (0.021)
9 Yrs After Flood	0.011 (0.027)	0.014 (0.016)	0.005 (0.019)	0.019 (0.008)**	-0.002 (0.019)
10 Yrs After Flood	0.042 (0.024)*	0.013 (0.015)	0.012 (0.013)	0.019 (0.011)*	0.011 (0.015)
11-27 Yrs After Flood	0.002 (0.028)	0.002 (0.022)	0.047 (0.019)	0.019 (0.023)	0.054 (0.034)
Media Mkt * Geo. Indicators	X	X	X	X	X
County Flood Indicators	X	X	X	X	X
Pre-Flood Indicators	X	X	X	X	X
Community FE	X	X	X	X	X
State-by-Year FE	X	X	X	X	X
Observations	268,996	268,996	268,996	268,996	268,996
Communities	9,607	9,607	9,607	9,607	9,607
R^2	.2064	.2083	.2074	.2066	.2080

Each column contains coefficients from a distinct regression of a version of Equation (2). The only difference from the regressions of Appendix Table 9 is that each of the regressions in this table include a set of event time indicator variables for whether a community is in the same TV Media Market (determined by Neilson Research Company) as a flooded community, as well as, a separate set of event time indicators for one of the five geographic neighbor designations and a set of event time indicators for whether a community is both in the same media market and a geographic neighbor. The interpretation of the coefficients in Panel A differ from those in Panel A of Appendix Table 9 in that they are point estimates for insurance take-up in communities that are in the same media market but not geographically close to the flood. The interpretation of the coefficients in Panel B differ from those in Panel B of Appendix Table 9 in that they are point estimates for insurance take-up in communities that are geographically close to a flood but not in the same media market. Columns (1)-(4) consider a neighbor to be a community in the 1,5,10, and 20 geographically closest counties to a PDD county. Column (5) defines a neighbor as a community in a county adjacent to a PDD county. Standard errors are corrected for the reduced number of degrees of freedom and clustered at the state level (significance level: *** 1%, ** 5%, * 10%). All regressions include: pre- and post-flood indicator variables, pre-flood indicators for neighboring communities, and state by year fixed effects. Refer to Section 3 of the paper and the Appendix Sections D and E.8 for details.

Table 11: (Online Appendix) Flood Insurance Take-up for Communities in Flooded and Neighboring Counties, by *County Geographic Rings*

	(1)		(2)		(3)		(4)		(5)		(6)	
Panel A: Presidential Disaster Declaration County												
Year of Flood	0.065	(0.013)***	0.064	(0.014)***	0.069	(0.014)***	0.064	(0.014)***	0.071	(0.013)***	0.083	(0.014)***
1 Yr After Flood	0.083	(0.014)***	0.083	(0.015)***	0.089	(0.016)***	0.083	(0.015)***	0.089	(0.015)***	0.101	(0.015)***
2 Yrs After Flood	0.078	(0.015)***	0.079	(0.016)***	0.086	(0.016)***	0.078	(0.016)***	0.086	(0.015)***	0.097	(0.015)***
3 Yrs After Flood	0.073	(0.014)***	0.073	(0.015)***	0.080	(0.015)***	0.075	(0.014)***	0.082	(0.014)***	0.093	(0.014)***
4 Yrs After Flood	0.072	(0.014)***	0.072	(0.015)***	0.078	(0.015)***	0.074	(0.015)***	0.080	(0.016)***	0.088	(0.015)***
5 Yrs After Flood	0.074	(0.016)***	0.073	(0.017)***	0.082	(0.016)***	0.079	(0.016)***	0.081	(0.018)***	0.089	(0.017)***
6 Yrs After Flood	0.058	(0.016)***	0.055	(0.016)***	0.062	(0.016)***	0.059	(0.015)***	0.059	(0.017)***	0.065	(0.017)***
7 Yrs After Flood	0.052	(0.015)***	0.051	(0.016)***	0.055	(0.015)***	0.053	(0.016)***	0.049	(0.017)***	0.054	(0.017)***
8 Yrs After Flood	0.049	(0.013)***	0.046	(0.013)***	0.051	(0.012)***	0.050	(0.011)***	0.045	(0.013)***	0.049	(0.015)***
9 Yrs After Flood	0.041	(0.014)***	0.038	(0.014)***	0.044	(0.013)***	0.042	(0.012)***	0.040	(0.014)***	0.046	(0.016)***
10 Yrs After Flood	0.039	(0.013)***	0.036	(0.013)***	0.043	(0.013)***	0.040	(0.012)***	0.037	(0.013)***	0.040	(0.015)***
11-27 Yrs After Flood	0.006	(0.023)	0.002	(0.023)	0.005	(0.024)	0.005	(0.023)	0.003	(0.023)	0.004	(0.022)
Panel B: County Neighboring PDD County and Not Hit by Flood												
Neighbor Def:	Closest 1		Closest 2-5		Closest 6-10		Closest 11-20		Adjacent		Media Market	
Year of Flood	0.024	(0.011)**	0.003	(0.010)	0.013	(0.004)***	0.004	(0.006)	0.017	(0.009)*	0.031	(0.006)***
1 Yr After Flood	0.025	(0.011)**	0.008	(0.010)	0.018	(0.006)***	0.006	(0.006)	0.018	(0.009)*	0.035	(0.005)***
2 Yrs After Flood	0.026	(0.010)**	0.012	(0.011)	0.022	(0.006)***	0.007	(0.007)	0.022	(0.009)**	0.033	(0.006)***
3 Yrs After Flood	0.032	(0.011)***	0.010	(0.012)	0.023	(0.006)***	0.012	(0.006)*	0.026	(0.010)**	0.036	(0.007)***
4 Yrs After Flood	0.028	(0.011)***	0.004	(0.011)	0.019	(0.007)***	0.010	(0.006)*	0.021	(0.011)*	0.030	(0.007)***
5 Yrs After Flood	0.029	(0.011)***	-0.001	(0.012)	0.021	(0.007)***	0.014	(0.005)***	0.018	(0.012)	0.028	(0.009)***
6 Yrs After Flood	0.015	(0.012)	-0.013	(0.011)	0.010	(0.007)	0.005	(0.005)	0.005	(0.010)	0.013	(0.007)*
7 Yrs After Flood	0.024	(0.010)**	-0.006	(0.013)	0.011	(0.011)	0.007	(0.005)	0.000	(0.012)	0.007	(0.009)
8 Yrs After Flood	0.033	(0.009)***	-0.009	(0.015)	0.011	(0.012)	0.009	(0.007)	-0.002	(0.011)	0.006	(0.011)
9 Yrs After Flood	0.029	(0.010)***	-0.012	(0.013)	0.011	(0.012)	0.007	(0.007)	0.001	(0.010)	0.009	(0.009)
10 Yrs After Flood	0.027	(0.011)**	-0.013	(0.013)	0.012	(0.012)	0.008	(0.009)	-0.001	(0.009)	0.002	(0.010)
11-27 Yrs After Flood	0.024	(0.018)	-0.040	(0.028)	-0.001	(0.017)	0.016	(0.016)	-0.011	(0.015)	-0.042	(0.037)
Pre-Flood Indicators	X		X		X		X		X		X	
Community FE	X		X		X		X		X		X	
State-by-Year FE	X		X		X		X		X		X	
Observations	268,996		268,996		268,996		268,996		268,996		268,996	
Communities	9,607		9,607		9,607		9,607		9,607		9,607	
R^2	.2047		.2050		.2049		.2046		.2051		.2061	

Each column contains coefficients from a distinct regression of Equation (2). All regressions include pre-flood indicator variables for flooded and neighboring communities. The designation of a flood is whether the community is located in a PDD County. Each regression uses a different definition of a neighboring community. Columns (1)-(4) consider a neighbor to be a community in the 1,2-5,6-10, and 11-20 geographically closest counties to a PDD county. Columns (2)-(4) differ from those in Appendix Table 8 in that the geographic counties are selected by increasingly distant "rings". Column (5) defines a neighbor as a community in a county adjacent to a PDD county. Column (6) defines a neighbor as a community in a county that shares the same TV media market as a PDD county. Refer to Section 3 of the paper and Appendix Sections D and E.8 for details.

Table 12: (Online Appendix) Flood Insurance Take-up for Communities in Flooded Counties, Geographically Neighboring Counties, and Counties in the Same TV Media Market, by *County Geographic Rings*

	(1)	(2)	(3)	(4)	(5)
Panel A: Media Market County Neighbor to a PDD Flood County					
Year of Flood	0.030 (0.006)***	0.031 (0.006)***	0.029 (0.006)***	0.032 (0.006)***	0.028 (0.007)***
1 Yr After Flood	0.034 (0.005)***	0.036 (0.005)***	0.032 (0.005)***	0.035 (0.005)***	0.032 (0.005)***
2 Yrs After Flood	0.032 (0.006)***	0.032 (0.006)***	0.029 (0.006)***	0.033 (0.006)***	0.029 (0.006)***
3 Yrs After Flood	0.035 (0.007)***	0.035 (0.007)***	0.032 (0.007)***	0.035 (0.007)***	0.031 (0.007)***
4 Yrs After Flood	0.029 (0.007)***	0.030 (0.007)***	0.027 (0.007)***	0.029 (0.007)***	0.026 (0.007)***
5 Yrs After Flood	0.027 (0.009)***	0.029 (0.009)***	0.024 (0.009)***	0.026 (0.009)***	0.025 (0.008)***
6 Yrs After Flood	0.013 (0.007)*	0.016 (0.007)**	0.012 (0.008)	0.013 (0.008)*	0.014 (0.007)*
7 Yrs After Flood	0.006 (0.009)	0.008 (0.008)	0.005 (0.008)	0.006 (0.009)	0.009 (0.008)
8 Yrs After Flood	0.005 (0.011)	0.008 (0.010)	0.004 (0.010)	0.005 (0.011)	0.009 (0.010)
9 Yrs After Flood	0.007 (0.009)	0.011 (0.008)	0.006 (0.008)	0.008 (0.009)	0.010 (0.009)
10 Yrs After Flood	0.001 (0.010)	0.004 (0.010)	-0.002 (0.009)	0.000 (0.009)	0.003 (0.010)
11-27 Yrs After Flood	-0.046 (0.036)	-0.034 (0.031)	-0.045 (0.036)	-0.051 (0.036)	-0.042 (0.037)
Panel B: Geographic County Neighbor to a PDD Flood County					
Neighbor Def:	Closest 1	Closest 2-5	Closest 6-10	Closest 11-20	Adjacent
Year of Flood	0.016 (0.011)	-0.005 (0.010)	0.005 (0.005)	-0.001 (0.006)	0.006 (0.010)
1 Yr After Flood	0.016 (0.011)	-0.001 (0.011)	0.009 (0.006)	0.000 (0.006)	0.006 (0.010)
2 Yrs After Flood	0.017 (0.010)*	0.004 (0.011)	0.013 (0.006)**	0.001 (0.007)	0.012 (0.009)
3 Yrs After Flood	0.022 (0.011)*	0.000 (0.012)	0.013 (0.006)**	0.005 (0.006)	0.014 (0.011)
4 Yrs After Flood	0.019 (0.011)*	-0.006 (0.011)	0.010 (0.007)	0.004 (0.006)	0.011 (0.012)
5 Yrs After Flood	0.020 (0.011)*	-0.011 (0.013)	0.013 (0.007)*	0.008 (0.006)	0.007 (0.012)
6 Yrs After Flood	0.010 (0.012)	-0.019 (0.011)*	0.006 (0.008)	0.001 (0.006)	-0.001 (0.010)
7 Yrs After Flood	0.021 (0.010)**	-0.010 (0.012)	0.008 (0.011)	0.005 (0.005)	-0.005 (0.012)
8 Yrs After Flood	0.030 (0.010)***	-0.014 (0.014)	0.009 (0.012)	0.006 (0.007)	-0.008 (0.011)
9 Yrs After Flood	0.026 (0.010)***	-0.017 (0.013)	0.009 (0.012)	0.005 (0.007)	-0.003 (0.011)
10 Yrs After Flood	0.028 (0.011)**	-0.015 (0.013)	0.013 (0.011)	0.009 (0.008)	-0.001 (0.008)
11-27 Yrs After Flood	0.031 (0.017)*	-0.035 (0.025)	0.012 (0.013)	0.027 (0.014)*	0.001 (0.015)
County Flood Indicators	X	X	X	X	X
Pre-Flood Indicators	X	X	X	X	X
Community FE	X	X	X	X	X
State-by-Year FE	X	X	X	X	X
Observations	268,996	268,996	268,996	268,996	268,996
Communities	9,607	9,607	9,607	9,607	9,607
R^2	.2063	.2065	.2063	.2063	.2065

Each column contains coefficients from a distinct regression of a version of Equation (2). The only difference from the regressions of Appendix Table 11 is that each of the regressions in this table include a set of event time indicator variables for whether a community is in the same TV Media Market (determined by Neilson Research Company) as a flooded community, as well as, a separate set of event time indicators for one of the five geographic neighbor designations. Columns (1)-(4) consider a neighbor to be a community in the 1,2-5,6-10, and 11-20 geographically closest counties to a PDD county. Columns (2)-(4) of this table differ from those in Appendix Table 9 in that the geographic counties are selected by increasingly distant "rings". Column (5) defines a neighbor as a community in a county adjacent to a PDD county. Standard errors are corrected for the reduced number of degrees of freedom and clustered at the state level (significance level: *** 1%, ** 5%, * 10%). All regressions include: pre- and post-flood indicator variables, pre-flood indicators for neighboring communities, and state by year fixed effects. Refer to Section 3 of the paper and the Appendix Sections D and E.8 for details.

Table 13: (Online Appendix) Flood Insurance Take-up for Communities in Flooded Counties, Geographically Neighboring Counties not in the same TV Media Market, and Counties in the Same TV Media Market and not in a Geographically Neighboring County, by *County Geographic Rings*

	(1)	(2)	(3)	(4)	(5)
Panel A: Media Market County Neighbor to a PDD Flood County & Not a Geographic Neighbor					
Year of Flood	0.031 (0.006)***	0.032 (0.007)***	0.032 (0.008)***	0.031 (0.007)***	0.036 (0.007)***
1 Yr After Flood	0.034 (0.005)***	0.035 (0.005)***	0.035 (0.006)***	0.034 (0.006)***	0.040 (0.005)***
2 Yrs After Flood	0.033 (0.006)***	0.033 (0.006)***	0.032 (0.006)***	0.034 (0.007)***	0.036 (0.006)***
3 Yrs After Flood	0.036 (0.007)***	0.038 (0.007)***	0.034 (0.007)***	0.041 (0.007)***	0.037 (0.008)***
4 Yrs After Flood	0.030 (0.007)***	0.033 (0.007)***	0.029 (0.008)***	0.035 (0.008)***	0.030 (0.007)***
5 Yrs After Flood	0.028 (0.008)***	0.033 (0.008)***	0.025 (0.010)**	0.032 (0.009)***	0.031 (0.007)***
6 Yrs After Flood	0.013 (0.007)*	0.018 (0.008)**	0.009 (0.008)	0.015 (0.008)*	0.015 (0.007)**
7 Yrs After Flood	0.006 (0.008)	0.011 (0.008)	-0.001 (0.009)	0.009 (0.010)	0.007 (0.008)
8 Yrs After Flood	0.005 (0.011)	0.013 (0.011)	-0.002 (0.011)	0.007 (0.012)	0.009 (0.011)
9 Yrs After Flood	0.007 (0.009)	0.016 (0.009)*	0.004 (0.009)	0.010 (0.010)	0.012 (0.010)
10 Yrs After Flood	0.001 (0.010)	0.008 (0.010)	-0.001 (0.009)	0.000 (0.011)	0.007 (0.011)
11-27 Yrs After Flood	-0.047 (0.036)	-0.031 (0.028)	-0.031 (0.030)	-0.049 (0.033)	-0.023 (0.029)
Panel B: Geographic County Neighbor to a PDD Flood County & Not a Media Market Neighbor					
Neighbor Def:	Closest 1	Closest 2-5	Closest 6-10	Closest 11-20	Adjacent
Year of Flood	0.026 (0.024)	-0.015 (0.018)	0.008 (0.008)	-0.001 (0.007)	0.020 (0.021)
1 Yr After Flood	0.012 (0.026)	-0.007 (0.019)	0.015 (0.008)*	-0.001 (0.009)	0.021 (0.021)
2 Yrs After Flood	0.046 (0.027)*	0.010 (0.017)	0.020 (0.010)**	0.003 (0.009)	0.028 (0.019)
3 Yrs After Flood	0.046 (0.028)*	0.016 (0.019)	0.019 (0.011)*	0.014 (0.010)	0.028 (0.020)
4 Yrs After Flood	0.036 (0.022)	0.009 (0.017)	0.016 (0.012)	0.013 (0.009)	0.020 (0.018)
5 Yrs After Flood	0.036 (0.022)	0.014 (0.019)	0.017 (0.013)	0.018 (0.010)*	0.021 (0.017)
6 Yrs After Flood	0.021 (0.026)	-0.018 (0.015)	0.000 (0.013)	0.005 (0.011)	0.001 (0.014)
7 Yrs After Flood	0.020 (0.030)	-0.004 (0.019)	-0.004 (0.020)	0.009 (0.011)	-0.015 (0.018)
8 Yrs After Flood	0.021 (0.028)	0.013 (0.026)	-0.006 (0.022)	0.009 (0.012)	-0.016 (0.021)
9 Yrs After Flood	0.011 (0.027)	0.011 (0.024)	0.004 (0.023)	0.008 (0.012)	-0.002 (0.019)
10 Yrs After Flood	0.042 (0.024)*	0.012 (0.022)	0.014 (0.017)	0.009 (0.015)	0.011 (0.015)
11-27 Yrs After Flood	0.002 (0.028)	-0.021 (0.024)	0.045 (0.025)*	0.029 (0.020)	0.054 (0.034)
Media Mkt * Geo. Indicators	X	X	X	X	X
County Flood Indicators	X	X	X	X	X
Pre-Flood Indicators	X	X	X	X	X
Community FE	X	X	X	X	X
State-by-Year FE	X	X	X	X	X
Observations	268,996	268,996	268,996	268,996	268,996
Communities	9,607	9,607	9,607	9,607	9,607
R^2	.2064	.2087	.2069	.2064	.2076

Each column contains coefficients from a distinct regression of a version of Equation (2). The only difference from the regressions of Appendix Table 12 is that each of the regressions in this table include a set of event time indicator variables for whether a community is in the same TV Media Market as a flooded community, as well as, a separate set of event time indicators for one of the five geographic neighbor designations and a set of event time indicators for whether a community is both in the same media market and a geographic neighbor. The interpretation of the coefficients in Panel A differ from those in Panel A of Appendix Table 12 in that they are point estimates for insurance take-up in communities that are in the same media market but not geographically close to the flood. The interpretation of the coefficients in Panel B differ from those in Panel B of Appendix Table 12 in that they are point estimates for insurance take-up in communities that are geographically close to a flood but not in the same media market. Columns (1)-(4) consider a neighbor to be a community in the 1,2-5,6-10, and 11-20 geographically closest counties to a PDD county. Columns (2)-(4) of this table differ from those in Appendix Table 10 in that the geographic counties are selected by increasingly distant "rings". Column (5) defines a neighbor as a community in a county adjacent to a PDD county. Standard errors are clustered at the state level (significance level: *** 1%, ** 5%, * 10%). All regressions include: pre- and post-flood indicator variables, pre-flood indicators for neighboring communities, and state by year fixed effects. Refer to Section 3 of the paper and the Appendix Sections D and E.8 for details.

Table 14: (Online Appendix) List of Important Media Events

Date	Description	Event Type
1/26/03	Super Bowl XXXVII	Politics
2/1/03	Columbia disintegration	Disasters
3/12/03	SARS	Disasters
3/19/03	Iraq War begins	Politics
12/13/03	Capture of Sadaam Hussein	Politics
2/1/04	Super Bowl XXXVIII	Sports
5/17/04	MA legalizes same-sex marriage	Politics
8/13/04	Summer Olympics begin	Sports
12/21/04	Attack on US military base in Iraq	Politics
2/6/05	Super Bowl XXXIX	Sports
4/2/05	Pope John Paul II dies	Politics
4/19/05	Pope Benedict XVI is elected	Politics
8/29/05	Hurricane Katrina makes landfall	Disasters
9/30/05	Muhammed cartoons in Danish newpaper	Politics
2/5/06	Super Bowl XL	Sports
2/10/06	Winter Olympics begin	Sports
6/9/06	World Cup begins	Sports
7/9/06	World Cup ends	Sports
2/4/07	Super Bowl XLI	Sports
4/16/07	Virginia Tech shooting	Disasters
8/1/07	Minnesota Bridge Collapse	Disasters
8/9/07	BNP Paribus withdrawl	Politics
9/1/07	Resignation of US Attorneys	Politics

These events are used as important media events that could potentially crowd out coverage of large regional floods. Table 15 presents the results of the regression that tests for crowding out of flood news coverage. Appendix Section E.9 provides more details.

Table 15: (Online Appendix) Evidence of Crowding Out News Stories on Floods During High Media Event Times

	(1)		(2)		(3)	
Specification:	Baseline Model		Media Market FEs		Media Market & Month FEs	
Panel A: Political and Sporting Events						
Flood	2.674	(0.356)***	2.648	(0.351)***	2.53	(0.342)***
Media Events	-0.056	(0.013)***	-0.056	(0.013)***	-0.137	(0.118)
Flood * Media Event	-1.414	(0.436)***	-1.395	(0.436)***	-1.307	(0.434)***
Observations	5,820		5,820		5,820	
R^2	.1803		.1803		.2365	
Panel B: Disasters and Sporting Events						
Flood	2.544	(0.348)***	2.508	(0.341)***	2.437	(0.335)***
Media Events	0.017	(0.019)	0.015	(0.018)	-0.153	(0.118)
Flood * Media Event	-0.831	(0.499)*	-0.766	(0.495)	-0.880	(0.464)*
Observations	5,820		5,820		5,820	
R^2	.1717		.1716		.2322	
Panel C: Disasters and Political Events						
Flood	2.474	(0.342)***	2.442	(0.334)***	2.353	(0.326)***
Media Events	0.052	(0.024)**	0.050	(0.023)**	0.068	(0.063)
Flood * Media Event	-0.527	(0.485)	-0.478	(0.476)	-0.527	(0.459)
Observations	5,820		5,820		5,820	
R^2	.1697		.1696		.2293	
Panel D: Disasters, Political and Sporting Events						
Flood	2.719	(0.402)***	2.680	(0.394)***	2.592	(0.387)***
Media Events	0.001	(0.016)	0.000	(0.0159)	-0.126	(0.122)
Flood * Media Event	-1.075	(0.499)**	-1.024	(0.493)**	-1.058	(0.482)**
Observations	5,820		5,820		5,820	
R^2	.1760		.1760		.2356	

The table presents the regression results for the flood news story crowding out analysis. There are 4 panels in the table and three columns (12 separate regressions). Each panel corresponds to a different grouping of news events. The news events are used to determine whether an important national news story occurred during the month. Table 14 lists the news events. The three columns show estimates using three different regression specifications. Column (1) doesn't include any control variables. Column (2) adds media market fixed effects. Column (3) adds month fixed effects. Standard errors are clustered by media market for all specifications.