Public Investment in Hazard Mitigation: Effectiveness and the Role of Community Diversity

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Abstract

How effective is public spending in reducing vulnerability to natural hazards? How much are communities investing out of their own budget and from federal grants? What are key driving factors? To answer these, I develop new measures of damages, weather risk, and spending for a panel of 904 US coastal counties in 2000-2020. I distinguish federally- and county-funded projects and rely on a quasi-experimental strategy, matching counties by economic development, population, and weather risk, to estimate the loss-reducing effect of local public investments. I use Microsoft's spatial building data and flood zone maps to provide precise measures of local vulnerability to weather losses. This is reflected in my severe-weather risk measure, which is based on predictions from the Random Forest learning algorithm, using granular data on resident vulnerability and severe weather frequency. My results provide evidence that public spending on adaptation is effective and efficient. In terms of effectiveness, I find that the average high-spending county avoids a significant portion of losses. In terms of efficiency, my results imply that $1 of spending reduces losses in the short term, or over the next five years, by $1.13. As investments remain longer in place, they continue to reduce further losses, and $1 of spending is expected to prevent close to $3 in losses over the next 20 years. I further find that the effectiveness of investments based on different funding can vary by the weather risk of the county: federal spending is most effective on high-risk areas, while local spending is effectively implemented in medium-risk counties. Finally, I show that fractionalization among residents about the priority of climate-change policy can be a limiting factor in adaptation spending. Total spending is significantly lower in areas with high diversity in policy preferences, and more so when opinions are equally split. This can explain why counties with similar weather risk may end up with different amount of public spending to reduce vulnerability.

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1 Introduction

Adaptation is key in reducing climate vulnerability caused by unsustainable patterns of development and socioeconomic inequity (Pielke et al., 2007; Ford et al., 2011). It is significantly cheaper to protect rather than abandon properties in simulations of climate change losses that allow for cost-effective adaptation (Martinich and Crimmins, 2019; Neumann et al., 2015, 2021). Adaptation options and ranking methods are widely discussed (Chambwera et al., 2014) but few studies systematically examine what measures are actually implemented.

How effective is adaptation? How much is spent and what motives it? Studies of specific projects imply that savings are low. A $261 million dune system saved $46 million in post-Sandy government liabilities, or $0.2 saving per $1 (Dundas, 2017).[1] New Orleans residents value a $10 billion Cat-5 levee at $118 million, or $0.01 per $1 (Landry et al., 2011). In contrast, probabilistic engineering studies suggest savings of up to $7 per $1 (MMC, 2019; Mechler, 2016). Finally, US panel studies of federal programs find savings between $1.15 and $7 (Davlasheridze et al., 2017; Davlasheridze and Miao, 2021; Healy and Malhotra, 2009).[2]

To add to this evidence, I compile new measures of damages, weather risk, and public spending for a panel of 904 US coastal counties during 2000-2020.[3] Federal funding is the focus of empirical work but is only one venue for municipalities to engage in adaptation. Municipalities can fund own projects to bypass the restrictive approval criteria of federal funding and more directly address community issues (Donahue and Joyce, 2001; Rose et al., 2007; Godschalk et al., 2009). Empirically, there is little evidence about the relative amount and effectiveness of county-funded projects (Fraser et al., 2003). To more comprehensively capture total public investment, I combine spending from two sources: Hazard Mitigation Grant Program (HMGP) and the "Natural Resources" category from the Census of Govern-

[1]The paper estimates that cost-saving based on the house price premium for buildings protected by the dune was $170, which implies $0.65 per $1 of spending.

[2]Variable definitions are not consistent between the papers: the first measures losses over a 4-year election cycle, the last two measure spending cumulatively and losses over a single year.

[3]Losses are due to hurricanes, flooding, and severe storms. Risk is expected loss from such events.

ment Finance and Employment (CGFE).[4] This measure implies that county-funded spending is significant – it represents about half of the .05% of GDP spent annually on adaptation.

The average loss-reducing effect of public investments is identified with a quasi-experimental strategy (Xiao and Feser, 2014). I choose this approach over just relying on county fixed effects because randomness in severe weather within a short panel can under/overestimate expected losses. In this study, I measure avoided damages – loss that would have occurred without adaptation – with the difference in losses between counties with different investment. To form an appropriate group of counties that reflect this counterfactual, I match by economic development, population, and – most importantly, weather risk. I incorporate risk predictions from the Random Forest learning algorithm, which are based on granular measures of resident vulnerability and severe weather frequency.[5]

Investment can reduce losses right away but whether savings materialize and how soon depends on the type and frequency of events that the project protects against. My empirical model focuses on the average losses over a five-year period as a function of spending in the previous: five years (short-term) or twenty years (medium-term). The medium-term analysis shortens the sample to 2010-2020 but limits the concern with reversion to mean in losses and gives investments time to "pay off" (Kunreuther and Michel-Kerjan, 2012).

I find that public spending on adaptation is effective – the average high-spending county avoids a significant portion of losses – and efficient – \$1 prevents close to \$3 in losses over 20 years.[6] This is surprisingly close to the probabilistic engineering estimates of savings from federal projects, despite the different empirical design (Mechler, 2016; MMC, 2019). However, my measure includes county-funded projects, which suggests that any public spending can be as effective as HMGP projects. There is evidence that savings from public spending depend

[4]HMGP designates federal funds to "rebuild in a way that reduces, or mitigates, future losses to communities". According to the Census, "Natural Resources" contains local spending focused on adaptation (Lee, 2021). It includes county-funded expenditures on regulation and management of natural resources, including for flood control, soil conservation, surveying and developing of water resources, etc.

[5]Risk is defined as expected losses, which are likely but may not occur every period. I use Microsoft's spatial building data and flood zone maps to provide precise measures of local vulnerability to weather losses.

[6]High-spending county is in the 95th percentile of spending. Losses are measured relative to county GDP.

on risk: they are sizable in medium-risk counties, but in high-risk ones additional spending does not reduce losses. Decomposing spending by funding source, I find that federal projects are very effective in high-risk counties, with \$57 saved per \$1, while county-funded spending plays a prominent role in medium-risk counties, saving \$9 for each \$1.

I explore why similar counties may choose different adaptation spending by focusing on social determinants emphasized in the literature on barriers to adaptation (Moser and Ekstrom, 2010). I test if divergent opinions about the priority of climate policy can reduce spending in the years after a direct impact.[7] There is evidence that counties increase spending as they become eligible for HMGP. However, higher diversity in policy preferences among residents reduces spending, particularly when opinions are equally split. This is consistent with Moser and Ekstrom (2010) and Adger et al. (2009) who argue that deep values/beliefs can be an important barrier which cuts across all phases in the process of adaptation.

The key contributions of my results are threefold. First, to my knowledge, my evidence is the first to show that locally-funded adaptation projects are deployed effectively and efficiently, and this happens predominantly in medium-risk counties. Since municipalities can spend from the budget not only when they are eligible for federal funding, this suggests that they proactively reduce their weather vulnerability. Second, there is evidence that federal spending has much higher effectiveness in high-risk areas compared to locally-funded projects. This implies that, at least from a national perspective, federal funding is allocated optimally. Third, I examine the dynamic effect and duration of adaptation benefits and show that spending saves, in the short and medium term, resulting in substantial and quickly realized savings over 20 years. My evidence is the first to quantify how quickly investment can "pay off", apart from engineering studies that estimate project lifetime savings.

The study proceeds as follows. Section 2 discusses relevant literature. Section 3 describes the data sources and the sample. Section 4 details the machine-learning procedure which

[7] I use data from the Yale Climate Opinion Maps (YCOM) on support for public policy related to climate change, i.e. should public policy be a priority, and examine whether county-level diversity and polarization can explain why some counties invest less.

estimates county risk. Section 5 studies the effectiveness of county mitigation. Section 6 examines the role of diversity. Section 7 includes extensions and robustness evidence. Section 8 concludes the paper.

2 Related Literature

This paper contributes to the literature on the effectiveness of public spending in reducing the impact from severe weather and climate change. Shreve and Kelman (2014) and Mechler (2016) review global case studies and find solid evidence in support of the economic effectiveness of disaster risk reduction.[8] MMC (2019, 2005, 2017); Rose et al. (2007) review the savings from individual FEMA-funded projects and find that the average $1 in spending saves $4/$7 in losses. Federal spending is also evaluated in three panel studies of US counties. Healy and Malhotra (2009) estimates that the average $1 spent on disaster preparedness over the previous two four-year periods reduces disaster damage by $7 in the current period. Davlasheridze et al. (2017) and Davlasheridze and Miao (2021) focus on hurricanes and floods for a subset of counties. Both quantify public investment as a cumulative sum from the start of the federal program and suggest that savings are $1.15/$1.8 per $1. My key contribution is in considering county-funded projects which are missing from these studies.[9] I find that these are non-trivial and are effectively implemented by municipalities. This can lead previous panel studies to under-estimate the effectiveness of federal projects, if funding sources are substitutes. I also examine the short/medium-term impact and quantify the duration of benefits. Davlasheridze et al. (2017) and Davlasheridze and Miao (2021) focus on cumulative spending, which cannot distinguish the role of earlier from recent spending. My empirical strategy models the level of weather risk in each county with a learning algorithm and granular data on vulnerability and hazard frequency, and identifies effectiveness relative to counties with similar risk. Davlasheridze and Miao (2021) divides the sample of counties

[8] According to Mechler (2016), average benefits are four times the cost.

[9] While a small portion of federal spending has to be matched by the municipality I show that locally-funded spending has an important impact even after holding federal spending constant.

by risk measured with flood zone shares, but weather risk is not part of the identification strategy. Finally, I use an original measure of losses based on estimates from relief programs and flood-insurance claims. These are county specific and do not allocate regional losses to counties with disaster declarations or impute economic losses from loss of environmental resources, as is done by the SHELDUS data used in all three panel studies.[10]

This paper also contributes to the literature on the cross-governmental efforts to build resilience to climate change. A review by Ford et al. (2011) notes that most adaptation is done at the municipal level, and in the sectors of transportations, infrastructure, and utilities, with only few studies that systematically examine actual adaptation. According to Neumayer et al. (2014), local government incentives to spend on mitigation are related to the expected losses. However, Donahue and Joyce (2001) notes that although local governments can most efficiently design and administer physical infrastructure, they often aim to shield residents from the cost by shifting it to the federal budget. At the local level there can also be a clear misalignment between who benefits from and who pays for protection Woodruff et al. (2020). Both contribute to an "adaptation deficit" (Adger et al., 2009; Moser and Ekstrom, 2010; Moser et al., 2012), whereby local government pursue incremental and flexible programs which aim to limit financial exposure (Carmin and Dodman, 2013) in the face of competing local priorities GAO (2009). My results add to the limited empirical evidence in this literature with the evidence that municipalities use their own budget to finance adaptation projects that are highly efficient. This is consistent with arguments that local spending focuses on robust, no-regret options that are highly efficient under different scenarios (Hallegatte, 2009). I show that county-funded adaptation mostly benefits medium-risk counties, contrary to the argument in Neumayer et al. (2014). In fact, high-risk counties appear to rely mostly on federally-funded spending.

[10] SELDUS stands for Spatial Hazard Events and Losses Database for the United States. See https://cemhs.asu.edu/sheldus/faq. For example: "Events reported by forecast zone: NWS forecast zones can consist of multiple counties or parts of multiple counties ... Whenever, a forecast zone covers multiple counties, SHELDUS™ equally distributes loss information across the counties within the forecast zone. NCDC does not distribute loss information across multiple counties belonging to the same forecast zone resulting again in an overestimation of losses for individual counties."

Finally, this paper contributes to the literature on the role of community diversity in the provision of public goods. A series of papers have explored the consequences of ethnically or culturally fractionalized communities showing that higher conflict reduces the provision of public goods.[11] Consistent with this literature, I find that counties with higher disagreement about climate policy priorities invest less in protection from severe weather. I show that this effect is particularly strong for spending out of the county budget, compared to for federally-funded investment. This adds an important empirical evidence to the largely theoretical or case-study literature on barriers to adaptation which argues that divergence in beliefs and preferences causes gridlock and limits spending (Adger et al., 2009; GAO, 2009; Moser and Ekstrom, 2010; Stirling, 2003).

3 Data Description

The data covers 904 counties in 14 coastal US states for the period between 2000 and 2020. I focus on losses due to hurricanes, floods, and severe storms.[12] The sample is aggregated at five-year periods with four county observations related to: 1) severe-weather losses; 2) hazard frequency and vulnerability; 3) public risk-reduction spending.

Severe-weather Losses: The estimate of county losses combines information specific to each county and disaster declaration from four sources. The Individuals and Households Program (IHP) lists damage assessed by property surveyors for uninsured residents in need of emergency repairs and relocation. Small Business Administration's (SBA) Disaster Loans program details residential and commercial losses to property/contents for those who borrow to finance repairs. FEMA's Public Assistance (PA) program estimates losses to public property, including roads, bridges, and hospitals.[13] National Flood Insurance Program (NFIP)

[11] See Alesina et al. (1999); Alesina and La Ferrara (2000); Alesina et al. (2000); Alesina and La Ferrara (2002); Alesina et al. (2003); Alesina and Ferrara (2005); Fulford et al. (2021)

[12] For a list of the states, county numbers, and summary statistics related to vulnerability of population and infrastructure, consult Table A1 in the appendix.

[13] A big component of this is related to the cost of cleanup of debris, which represents a key loss from natural hazards. I use PA data which lists individual counties as recipients under a given disaster declaration.

lists insured flood-related losses based on residential/commercial insurance claims.[14]

The five-year weather-related loss averages 0.5% of GDP and can reach 1.5% for high-risk counties according to Table 1. The biggest component (44%) is made up by loss from the SBA data, with the other three sources comprising about 20%. Figure 1 highlights the fat-tail-type distribution of losses: 10% of counties have 0.5%-1.8% loss, 4% have 1.8%-4.25%, and about 3% have losses over 4.25%. The spatial distribution of losses in Figure 2 highlights the consistency with which similar areas are impacted during the sample. PA and SBA losses are most widespread and insured flood damage is dominant in coastal areas. IHP losses are localized and comprise a smaller proportion as they target low-income communities.

Hazard Frequency and Vulnerability: Hazard frequency is inferred from the count of disaster declarations due to hurricanes, floods, and severe storms during the five previous 5-year periods.[15] Hurricanes have a higher recurrence for a subset of counties but for most they are fairly infrequent. The average county has 0.05, 0.2, 0.4 hurricanes 20-25 /15-20/10-15 years ago, according to Table A2, suggesting an increase in severe weather.

Resident vulnerability is inferred from the fractions of buildings in the 100-year (A), 100-year direct impact (V), and 500-year flood zone (B); within 200 and 1000 yards of water; with insurance; and median flood-insurance CRS discount for buildings in each flood zone.[16] Fractions are calculated by overlaying Microsoft's Building Footprints data over flood zone maps or maps of bodies of water.[17] CRS discounts are from data on flood-insurance purchases, provided by FEMA, which lists individual flood insurance purchases by census tract and year of purchase, as well as the flood zone and CRS discount applied.

Additional vulnerability data is from the 2000 US Census Block Group variables, as fractions, including: seasonal-use housing, house value over $1M, house value between $750K-

[14] I match a flood loss to a disaster declaration if it occurred within 30 days of the initial declaration date. In the case when there are more than one declarations within the county, I use the first event. Finally, I drop flood claims of less than $100 and drop counties with less than $50K in total claims.

[15] This information comes from FEMA's list of presidential disaster declarations.

[16] The CRS discount increases when communities engage in measures to prevent flood risk.

[17] Microsoft's Building Footprints are from: https://www.microsoft.com/en-us/maps/building-footprints. Bodies of water maps are from the US Census. For fraction insured, I compare the number of flood insurance in each flood zone from the NFIP data to total buidlings.

$999K, housing built 1999 to 2000, vacant housing, housing with 50+ units, housing with 20 to 49 units, rural, below-poverty, and aged 65+ population. I measure each variable separately for the A, V, B flood zones, and for non-flood-zones.[18]

Both geographic factors, such as hurricane frequency, and socio-economic factors, such as population in flood zones, are responsible for the spatial patterns of losses in Figure 2. Resident vulnerability to losses is highly variable, as captured by the standard deviation and the 90th percentile in Table 1: 5.3% of housing is in a 100-year flood zone but at the 90th percentile this approaches 13%; 13.8% of housing is 200 yards from water but at the 90th this approaches 30%. These numbers are significantly higher in high-risk counties. Table A1 highlights the large vulnerability differences even for states with similar hurricane frequency.

Public Risk-reduction Spending: Public spending on adaptation to weather risk comes from two sources: the federal and county budget. Federal spending is from the Hazard Mitigation Grant Program (HMGP). It designates an amount proportional to previous disaster-declaration losses to "rebuild in a way that reduces, or mitigates, future losses to communities".[19] Spending is listed by the type of project, the county which received the funding, and the date on which the project was started and finished.[20] I use the universe of projects post 1995, excluding: those with over four types of mitigation (1.25%);[21]; lasting over ten years; types used in less than 15 counties or totalling below $20M in the sample.

Spending from the county budget comes from the "Natural Resources" category listed in the Census of Government Finance and Employment (CGFE). It is considered as the main funding source for adaptation spending (Lee, 2021) and includes "Irrigation; drainage; flood control; soil conservation and reclamation including prevention of soil erosion; surveying, development, and regulation of water resources; wetlands and watershed management and protection; geological surveying and mapping; purchase of land for open space and conserva-

[18] I do this by measuring the (area) proportion of each Block Group that falls within a specific flood zone.

[19] https://www.fema.gov/grants/mitigation/hazard-mitigation.

[20] Projects can: retrofit private/public buildings, utility, infrastructure, to make them less susceptible to future damage; can purchase hazard-prone property; reduce flood impact with flood-control methods.

[21] 84% of the funding in the sample is dedicated to single-type projects. I divide funding equally for those involving more than one type.

tion programs; dam and reservoir safety; public education programs related to the above."[22].

Spending is measured as the annual average over a five-year period, relative to county GDP at the start of the period. I do not observe when HMGP grants are spent – only the start/end date, and cannot verify when the project starts to actively protect a community. My measuring choice makes HMGP consistent with the CGFE spending which reflects annual local government expenditures. Both measures are available starting in 1995. The average adaptation spending is .05%, equally split by federal and local funding, according to Table 2. The top 5% (High Mitigation Spending) spend close to 0.6%. Those with high federal spending (top 10% with HMGP) spend about 0.6%, while those with high county spending (top 5% with county spending) spend 0.2%. The spatial distribution is mapped in Figure 3 and suggests that risk-reduction spending is widely used across the states in the sample. Figure 6 plots spending by state risk quintiles. The total and each component increase with weather risk, suggesting that communities faced with higher likelihood of losses generally spend more to reduce their exposure. The fact that "Natural resources" spending also increases alleviates the concern that it may not reflect adaptation activities.

Additional Data: I use data on climate beliefs from the Yale Climate Opinion survey, which details average responses for a range of climate-related questions. The data provides county averages for responses. I measure the diversity in responses regarding climate policy priority based on the HHI formula: $diversity = 1 - \sum_i s_i^2$, where s_i are shares responding high, medium, and low. I also calculate a measure of polarization based on the formula: $pol = 1 - \sum_i (\frac{.5 - s_i}{.5})^2$. Finally, GDP, employment, and population data comes from the BEA.

Sample Selection: The sample includes observations for 904 counties in 14 states aggre-

[22]This definition is from the US Census - Government Finance and Employment Classification Manual. It also includes "regulation of mineral resources and related industries (e.g. gas and oil drilling) including land reclamation" It should be noted that local spending under the Natural Resources category can somewhat overestimate mitigation spending since it includes funding for the "conservation, promotion, and development of natural resources", according to the Census definition (https://www.census.gov/programs-surveys/gov-finances/about/glossary.html#par˙textimage˙477772327) It is distinct from expenditures on "Parks and Recreation", "Sewerage", and "Solid Waste Management", which are also related to the local environmental spending but do not necessarily fund activities aimed at preventing future losses (Lee, 2021) The definition closely matches project types outlined in the HMGP and so represents a locally-funded alternative to federal projects.

gated at five-year intervals starting from 2000 to 2020. I exclude counties: at the bottom 10% of the population distribution as of 2000; without a flood zone; with total damage in the top 1% of the distribution across all counties.[23]

4 Predicting Losses and County Risk Categories

In this section, I discuss the measure of long-term county weather risk, which helps define constant groups of counties with similar characteristics. First, I examine the relevance of hazard frequency and vulnerability variables in explaining weather loss by focusing on cross-sectional OLS coefficients. Then, I turn to the Random Forest algorithm to predict losses, which are the main focus of the paper.

4.1 Main Drivers of Weather-related Losses: OLS Evidence

To provide evidence for the role of hazard frequency and vulnerability for observed damages, I estimate cross-sectional models of loss with state indicators, which allow for time-invariant county characteristics.[24] Estimates are provided in Table A3 in the Appendix. The specification in Column (1) includes five disaster declaration lags, listing the first lags and plotting the rest in Figure A1. Historical occurrence of severe weather is an important predictor of losses suggesting that hazard frequency matters. In addition, vulnerability plays an important role, as seen in Column (2), which adds variables for fractions of housing in flood zones, close to water, and CRS discounts. Higher fractions in flood zones or close to water increases losses, while more strict flood-risk management (higher CRS discount) reduces them.[25] Column (3) includes additional vulnerability variables from the Census and Column (4) divides them by A, V, B flood zones and outside of flood zones. We see that vacant or rural housing increases losses, while more expensive and/or housing with more units reduces losses.

[23]I remove the top 1% since their losses are fairly exceptional and mean reversion paired with higher supply of funding for mitigation can overestimate the effectiveness of mitigation investments.

[24]For discussion of vulnerability see Cutter et al. (2003); Haque and Etkin (2007); Sant'Anna (2018).

[25]The negative CRS effect is reflected in coefficient of the squared term.

Both weather hazard frequency and vulnerability are critical in explaining observed losses. To examine the relative importance of each, we can compare the R^2 across the different models in Table A3. The model with state indicators and historical occurrence of severe weather can explain almost 10% of the observed variation in losses. Adding the vulnerability variables increases this by 50%, suggesting that both are critical.

4.2 Modeling County Risk with a Learning Algorithm

I predict county loss with the Random Forest (RF) learning algorithm, which is based on the concept of regressions tress. The general idea behind regression trees is to divide the predictor space into non-overlapping regions and assign the average of the response as the predicted value associated with each region (James et al., 2013). The cutoffs defining the non-overlapping regions are chosen to minimize the sum of squares of the difference between actual and predicted values. The Random Forest (RF) model is a variation of regression trees which limits and randomizes the set of predictors used to split the predictor space (Hengl et al., 2018; James et al., 2013) in order to limit overfitting of the data.

RF is frequently used in environmental modeling due to its superior predictive performance (Schratz et al., 2018). It is suitable for the current application for three reasons. First, it accounts for non-linear relationships between the predictors, predictor interactions, and outcome.[26] Second, it is more flexible when dealing with spatial correlation by using spatial cross-validation, i.e. train the model on spatially disjointed areas. Third, it prioritizes the "closeness" of its prediction over identifying and interpreting key factors.

I teach the algorithm to predict five-year losses separately for each state from 70 variables: 15 lags of disaster declarations for hurricanes, flooding, and severe storms; 11 variables for the fraction of housing in A, B, X flood-zones, fraction of insured in each zone, CRS discount in each zone, and fraction within 200 and 2000 yards of water; 44 demographic/housing

[26]For example, the fraction of housing in the 100-year flood zone can be associated with higher losses at lower levels and lower losses at higher levels if unobservable community measures reduce losses when exposure to losses is high. Similarly, more flood zone housing can reduce losses if those are multi-floor buildings which are generally more resistant to flooding.

variables from the 2000 US census (described in the Data section). I tune three hyper-parameters controlling the randomness of the model and use spatial cross-validation.[27]

The predictions from the model can be interpreted as expected loss given the resident vulnerability and frequency of severe weather. They capture weather risk, which can be defined as the potential for severe weather to cause adverse effects on economic conditions (Council et al., 2014). Figure 4 maps the time-varying predicted values. The algorithm identifies areas where losses are likely. Whether they actually occur depends on the underlying frequency of severe weather. Generally, counties with higher vulnerability and risk of high losses will not experience high de-facto losses in each five-year period.

In Figure 5, I map two different (state) risk ranks using the sample median of expected risk. Both reveal clusters of counties with similar loss potential, which are key in the empirical design. Table A4 in the Appendix provides some additional evidence about the relationship between the predicted loss and the actual using a cross-section OLS estimation. Column (1) highlights that correlation between the two. Column (2) uses indicators for risk quarterlies and shows that counties of higher risk quartile on average experience higher actual loss. The rest of the columns help distinguish the key factors driving the RF predictions.[28] Historical events, flood zone presence/management, insurance rate, and population density are associated with predicted damage as they are with actual loss in Table A3.

5 How Effective Is Public Risk-Reduction Spending?

There is a wide array of strategies to reduce losses from natural hazards: (a) hard (e.g., seawalls, revetments, and breakwaters) or soft structural protection measures (e.g., beach

[27] I divide counties into five spatially-disjointed subsets and estimating a regression tree for each subset based on a random pick from the possible range of hyper-parameters. The hyper-parameters are: number of predictors in each tree; fraction of observations used in each tree; number of observations in each terminal node. The range of each is respectively: [1, 69]; [0.2, 0.9]; [1, 10]. Spatial clustering uses k-means clustering based on the centroids. I do a random search over the hyper-parameter space by iterating 4,000 times and use the average root mean squared error across the five spatially-disjointed subsets to select parameters. The predictions are based on the averaged predictions for the regression trees from each subset.

[28] The RF model is highly non-linear – an advantage in the current setting – and interpreting which factors are key drivers is challenging. Linear regressions are only an approximate summary.

replenishment); (b) nonstructural measures (e.g., flood insurance, stricter building codes, elevating structures, wetlands); and (c) relocation (e.g. buy-outs) (Moser et al., 2012). Weather risk reduction is considered a public good which improves social welfare and is generally publicly financed (Bisaro and Hinkel, 2018). Here, I focus on projects financed by counties' own budgets as well as through the federally-backed HMGP. According to Fraser et al. (2003) these are the two main funding sources to pursue local adaptation.

Not all feasible risk-reduction projects are desirable – some adaptations are undesirable because of their high welfare opportunity cost (Chambwera et al., 2014). They can differ in terms of risk reduction benefits, costs, or ecosystem impacts (Council et al., 2014), and there are several approaches to rank the relative merit, including cost-benefit or effectiveness (Smit and Wandel, 2006). Cost-benefit is based on economic principles suggesting that optimal adaptation equalizes the marginal adaptation cost and benefit.[29] Alternatively, communities can focus on the level of acceptable risk and develop cost effective strategies to meet this level (Council et al., 2014). Measures with lower acceptable risk prevent more losses but cost more and often fail standard efficiency criteria (Hallegatte, 2006; Mendelsohn et al., 2020).

I focus empirically on benefit-cost ratios (BCR) – avoided loss relative to cost – and interpret high values as suggestive of adaptive decisions focused on no-regret or "low-hanging fruit" options that are lower cost but are beneficial in multiple scenarios (Moser et al., 2012). Low ones are consistent with investments that minimize the risk and/or over-provision of protection. Cost can still play a role in the choice of acceptable risk since municipalities can choose higher risk to reduce their spending, which increases BCR.

5.1 Empirical Strategy

My empirical strategy identifies the average BCR for public investments with a quasi-experimental setup. I quantify the difference in losses across counties with similar characteristics, but which have different amount of public spending and assume that this reflects

[29] Uncertainty in predicting weather risk can also be incorporated with robustness, no-regret, or safety margin principles (Hallegatte, 2009).

avoided damages. The key challenge is to properly measure the loss that would have occurred had the county not invested. To do this, I focus on a comparison group of counties which have very similar economic development, population, and – most importantly, similar weather risk. Why would similar counties not invest similar amounts? Municipalities may prefer to address more immediate issues, such as municipal traffic or daycare provisioning, which are often more salient local concerns, and thus offer immediate rewards to public actors addressing them (GAO, 2009; Storbjörk and Hedrén, 2011; Bisaro and Hinkel, 2018).[30]

Identifying the underlying weather risk at each county is key in my empirical design. This can be done with county fixed effects that control for time-invariant differences in investment and in losses. However, randomness in severe weather can lead to damage in otherwise low-risk counties and leave high-risk ones unaffected. As a result, county FE can both over and underestimate risk, particularly in short panels. The importance of properly controlling for risk can be seen in Figure 7, which plots the empirical relationship between spending and losses by risk. Spending reduces losses *relative to the group with the same risk*. Furthermore, the marginal impact of spending quickly declines particularly in low-risk counties.

My preferred approach incorporates the risk measure predicted by the RF learning algorithm. I use the k-means clustering algorithm to allocate counties within each state into groups that are closely matched according to their population, income, and risk. The algorithm allows me to specify the number of possible groups and I experiment with this parameter, as well as with using only risk to group counties. Table A5 lists the twenty clusters for Florida along with the averages for each cluster. There is dramatic variation across clusters underscoring that not all losses can serve as a counterfactual. Table A6 showcases the set of counties comprising cluster 18 from Table A5. They have similar income, expected loss, and population, and all experience similar damages, which ensures that they have accesses to similar amount of federal funding.

In principle, investment should reduce losses after the project is completed. In practice,

[30] About 71% of the officials who responded to the GAO questionnaire rated "non-adaptation activities are higher priorities" as very or extremely challenging (GAO, 2009).

whether such loss savings materialize and how soon depends on the type of events that the project is designed to protect against and how frequently the county is affected by such events. My empirical model focuses on the average de-facto losses over a five-year period as a function on mitigation spending in prior five-year periods. The short-term specification focuses on spending 5-10 years ago and the medium-term one goes back to 20 years.

5.1.1 Short-term Impact

The short-term impact of mitigation spending is reflected in the immediate reduction in losses after projects are completed. This effect is likely to be important for counties with significant recurring losses, for example, caused by frequent flooding. The HMGP data starts in 1995 which allows me to identify only the short term impact for counties subject to the severe hurricanes in the early 2000s. I estimate variations of the following specification:

$$\begin{aligned}\text{Damage}_{c,t} = &\ \gamma 1(\text{High Spending})_{c,t-5} + \eta 1(\text{Medium Spending})_{c,t-5} \\ &+ \sigma \text{PDD}_{c,t\in[-5:-25]} + \beta X_{c,t-5} + \text{PeerGroup}_c \times \alpha_t + \alpha_c + \epsilon_{c,t}\end{aligned} \tag{1}$$

$\text{Damage}_{c,t}$ is county c's total loss over a five-year period, starting at t. $1(\text{High Spending})_{c,t-5}$ is an indicator variable for counties with top 5% investment in the previous five-year period. $1(\text{Medium Spending})_{c,t-5}$ is an indicator for investment between the 75th and the 95th percentile. $\text{PDD}_{c,t\in[-5:-25]}$ represents the set of distributed lags of the count of presidential disaster declarations related to hurricanes, floods, and severe-storms going back to 25 years prior. $X_{c,t-5}$ includes lagged logs of population, personal income, and employment.

α_c is a county fixed effect and $\text{PeerGroup}_c \times \alpha_t$ refers to an indicator for the peer group that includes c, interacted with a year indicator. PeerGroup_c includes the same set of counties over the sample. I experiment with several different criteria to define groups: state decile of county loss predicted from an OLS model; state deciles of the loss predicted by the learning algorithm; k-means clustering using loss predicted by the learning algorithm; k-means clustering using loss predicted by the learning algorithm, per-capita income, and population. This grouping is the basis for the quasi-experimental control group setting where the counterfactual is estimated from the losses of counties with similar risk characteristics.

The effect of high/medium investment is captured by γ/η, respectively, and is identified within a single-difference setting. γ represents the difference in the average loss during a five-year period for high investment counties relative to the period-average for all counties in the peer group with lower investment.[31] Negative γ implies that a county with a higher investment 5-10 years ago has lower losses during the current five-year period compared to the losses of counties with similar risk but lower investment, after controlling for each county's long-term average via the county FE. Assuming that investment reduces damages, counties with high spending start with similar expected losses as their peers prior to the investment and experience lower losses afterwards, which is reflected in the estimate of γ.

There are two important concerns. First, counties with higher losses during the previous five-year period can be eligible for higher federal funding and end up in the high-spending category. If higher losses during the previous five-year period are more likely to be followed by lower losses in the next period due to mean reversion in damage, γ/η will not identify the risk-reducing impact of investment Davlasheridze et al. (2017); Healy and Malhotra (2009)). There are several factors that address this. Because counties in the peer group are spatially clustered (see Figure 5) and have similar risk/economic development/population (see Table A6), they experience similar losses and are subject to similar mean reversion. In this case γ/η are identified as the investment-driven reduction in losses above and beyond the reduction due to reversion which is characteristic to all counties in the group. The distributed lags of past severe weather also control for the frequency of hazards, i.e. that the probability of severe weather declines in the period right afterwards. In the robustness section, I include past period losses, which does not change the main results, suggesting that the quasi-experimental design is effective at limiting the effect of mean reversion. Second, counties may engage in other methods of adaptation, such as private investment or changes

[31] Note that if all counties fall within the same spending category, the effect be subsumed by $\text{PeerGroup}_c \times \alpha_t$ and not identified.

in land-use enforcement, which are not captured in the empirical model. Since willingness to pay to reduce future losses is positively correlated with income (Pavel and Mozumder, 2019), I am careful to match counties with similar income in the peer groups to minimize potential difference in private investments. While I cannot directly control for the level of enforcement, I can account for any municipal efforts to reduce future losses that are associated with higher county spending under the natural resources category.

5.1.2 Medium-term Impact

When reducing risk, protection is only evident after severe weather. Figure 2 shows that significant losses occurred in different areas in each of the four sample periods: Florida/Alabama counties saw high losses during 2000-2004, Gulf coast counties were affected during 2005-2009, and the North-east counties during 2010-2014. Investments during 1995-1999 might not reduce any losses in the following period in the Northeast but can have an important impact in Florida. At the same time, they may "pay off' and reduce losses in the Northeast three periods later, when the area is hit by severe weather.

To investigate the longer-term impact of investments, I focus on the two five-year periods starting with 2010, which allows me to incorporate investments over the previous 20 years. This significantly shortens the sample and omits the historical hurricanes in the early 2000s. However, it affords the longer time horizon over which the majority of investments are expected to save losses.[32] I estimate variations of the following specification:

$$\begin{aligned}\text{Damage}_{c,t} = \sum_{j=5:15} & \gamma_j 1(\text{High Spending})_{c,t-j} + \eta_j 1(\text{Medium Spending})_{c,t-j} \\ & + \sigma \text{PDD}_{c,t\in[-5:-25]} + \beta X_{c,t-1} + \text{PeerGroup}_c \times \alpha_t + \alpha_c + \epsilon_{c,t}\end{aligned} \tag{2}$$

where variable definitions are as in the short-term specification above. The specification includes a set of distributed lags of indicators for High and Medium Spending for the three

[32]Still, it should be noted that 20 years is shorter than the 50-year life of some hard or soft-structural adaptation measures (Aerts, 2018; Mendelsohn et al., 2020).

five-year periods preceding the current one. I focus on three lags of investment because this is the maximum number which still allows me to estimate county fixed effect.

γ_{10} represents the effect of high spending in past 10 to 15 years on current losses. Identification is based on a similar single-difference specification. It compares the difference in current losses for counties with high spending 10-15 years ago relative to losses by counties with lower spending. Peer groups follow from the short-term specification. Since the sample here includes only two periods, the county fixed effect is less likely to reflect county weather-related risk. This makes the inclusion of the quasi-experimental control groups more critical in order to capture the appropriate counterfactual for counties with higher investment. This ensures that a higher-risk county with high losses in 2000-2010 (not in the sample) and limited losses in 2010-2020 is still compared to its appropriate peers.

The medium-term specification provides two important advantages. First, the concern with loss reversion is less important here, particularly for longer lags of investment, since high losses 15 years ago are not likely to be followed by limited losses in the current period. In fact, Figure A1 suggests that disaster declarations 15 years prior are predictive to losses in the current period. Second, it provide a longer period of evaluation over which investment can reduce losses and explicitly considers whether the protection of historical investment depreciates over time. The latter is of interest in the context of climate change which can change the pattern of weather hazards.

5.2 Estimation Results

5.2.1 Short-term Estimates

Estimates from model (1), with different peer group definitions, are listed in Table 3. In Column (1), where all counties in the state serve as a comparison, high spending 5-10 years ago reduces current losses by 0.46%. Medium spending reduces losses by 0.1%, which is not statistically significant. Dividing 0.46% by 0.55% (average spending at high-spending counties) – yields a BCR of 0.83, implying that \$1 saves \$0.83 of losses.

Column (2) groups counties by the decile of predicted loss using the OLS model discussed above,[33] and Column (3) uses the predicted loss from the RF learning algorithm. High spending reduces losses by .51% and .4%, respectively, with BCR of .93 and .72. Column (4) uses the risk measure from (3) but relies on k-means clustering to group counties.[34] It gives the lowest effectiveness – high-spending reduces losses by 0.33%, yielding a BCR of 0.6.

The results imply that adaptation spending is not efficient from a simple cost-benefit perspective – $1 saves between $.6 and $0.93. Part of this is due to the short-run focus, during which investment may not "pay off", unless severe weather is frequent or occurs right away. In addition, counties may adapt to weather with private investments, regulation, or migration, which can underestimate the effect of public investment if the two are substitutes. To control for these, I assume that private adaptation is correlated with economic development, with richer counties being more likely to invest privately. I also assume that more populous counties are more likely to rely on public spending due to its higher efficiency in places with higher density. I expect that matching counties by risk, income, and population, in Column (5), limits the importance of unobservable adaptation. The results suggest that high-spending reduces losses by .62%, or a BCR of 1.13, which is economically efficient. The higher estimated benefit provides evidence that counties engage in private adaptation, which, when not controlled for, can lead to underestimated effects of public spending.

Columns (6) and (7) use the continuous measures of spending, along with squared terms to control for diminishing returns. The coefficient estimates can be read directly as BCRs because $1 represents the same proportion of spending and losses (relative to GDP). Without controlling for alternative adaptation measures, coefficients in Column (6) are lower, while with the controls, the BCR estimate in column (7) is 1.25.

The estimates from my preferred specification (5), or (7), reflect the short term savings from protection but are still close to Davlasheridze et al. (2017), who find that $1 of federally-

[33]The estimates from this model can be seen in column (4) of Table A3. I use the sample median prediction for each county and rank each county by the state decile.

[34]I allocate counties into 15 groups in each state, except for MA, MD, and NJ which use 10 groups.

funded spending (only one component of my measure) reduces losses by $1.15. However, Davlasheridze et al. (2017) estimates this saving at an annual per capita basis and measures investment cumulatively. This makes it harder to compare with my results. My estimates are lower than Healy and Malhotra (2009), who conclude that $1 in spending reduces losses by about $7. However, the paper considers all types of disasters in an earlier period and only measures federal spending.

5.2.2 Medium-term Estimates

Medium-term results are listed in Table 5. In Column (1), all lags for high spending have a negative estimate but are not significant. Investment 15 to 20 years ago appears to depreciate quickly – counter to the longer lifespan quoted in the literature (Aerts, 2018). Because the specification mixes counties with different weather risk, the effect is likely underestimated. Column (2) rectifies this, using k-means clustering and risk predictions from the learning algorithm. High investment 15-20 years ago reduces losses by 0.68%, with a BCR of 1.25 (0.55% average spending). High spending 10-15 years ago reduces losses by 0.45%, or a .82 BCR, while most recent investment has almost no impact. Cumulatively, high investment in a given period is expected to reduce losses over the next 5 to 20 years by 1.2%, with an implied BCR of 2.2. This estimate is highly statistically significant.

In Column (3), with control groups matched by risk, development, and population, high investment in all three past periods reduces current losses by 0.43%, 0.62%, 0.56%, from the most recent to the earliest. The cumulative impact of high investment is to reduce losses over the next 5 to 20 years by 1.6%. $1 is expected to save $3 in losses. This is close to the $4-$6 in saving estimated by MMC (2005, 2017) using the universe of individual federally-funded projects. My measure includes county-funded investments, and so provides the first evidence that municipalities can fund their own, highly effective protection projects. Investments protect from losses right away and remain protective for at least 20 years.

Estimates using continuous measures, in Columns (4) and (5), provide a similar picture with some differences. The cost efficiency of adaptation is higher – between 2.5 and 3.9. Note that the specification allows for non-linearity with squared terms for spending, which are not included in the table but are positive. Some high-spending municipalities may target a lower level of acceptable risk, which can raise costs with limited additional benefits, and reduce BCR. For examines of this see Dundas (2017); Hallegatte (2006); Mendelsohn et al. (2020). Notably, in Dundas (2017) the 22-ft tall engineered dune system in Harvey Cedars, NJ, cost \$261 million but saved \$58 million during a 700-year storm event, compared to a nearby community without this investment, yielding a BCR of 0.22. Using homeowners perceived savings, reflected in house prices, the dune system has a BCR of 0.65.

5.2.3 Estimates by County Risk

How does the potential for losses dictate the types of protective projects that are implemented? Since they are public goods, the choice of specific projects will involve political factors (Prater and Lindell, 2000). I expect that higher risk reduces the local political costs of investing in prevention (Neumayer et al., 2014). High-risk municipalities may opt for costly – and economically inefficient – protection against low probability-high impact storms, such as a 500-year levee (Fell and Kousky, 2015) or sea-wall (Mendelsohn et al., 2020). Medium-risk counties, where the political cost of over-investing can be higher, may focus on "low-hanging fruit" and implement high-efficiency adaptation. However, in light of the uncertainty in future losses and differences in local preferences for publicly-funded protection, the relationship between risk and protection effectiveness can be varied. For example, Landry et al. (2011) find that New Orleans residents are willing to pay up to \$181 million for a Category 5 levee which is estimated to cost \$10 billion.

In Table 5, I divide the sample by risk and re-estimate the specification with counties matched by risk, income, and population. The estimates for high-risk counties, in Column (1), suggest that high spending does not reduce losses. Why is spending not effective? First, counties may not experience severe weather and protection is not "tested". Second, low-spending counties can offset public with private spending. Third, drivers of loss or vulnerability can evolve and depreciate the effectives of protection. Fourth, only federally-funded spending may be effective if high-risk counties use self-financed projects to address other municipal needs.

I have experimented with including only counties subject to losses or states with severe weather but find that results are similar, suggesting that the first explanation is not likely.[35] My definition of peer groups limits the importance of private spending. In fact, estimates with only state-year FE (not included here) are more positive, implying that peer groups account for private spending. However, I cannot fully rule out this explanation. My results can be an indication that older mitigation measures less effective. It is widely acknowledged that high-risk areas have attracted significant migration in the US (Hallegatte, 2017; Pielke Jr et al., 2008). Since the most recent spending has the highest negative estimate, the evidence is consistent with the fact that adaptation is not a static concern (Hallegatte, 2009), with optimal strategies changing over time (Chambwera et al., 2014). Below, I examine the last hypothesis that only some type of spending is effective in high-risk counties.

Column (2) includes counties in the 40th to 80th risk percentile. The results are very close to the baseline estimates, suggesting that the majority of benefits from investments are realized by counties in the middle of the risk distribution. High spending reduces losses cumulatively by 1.36% over the next 5 to 20 years, with a BCR of 2.5.[36] This suggests that adaptation is under-provided (Chambwera et al., 2014) and $1 of spending, on average saves slightly over $2.5 in losses over the next 20 years.

The sample in Column (3) includes the remaining low-risk counties. Only recent investment shows a negative and statistically significant effect, and the implied BCR is close to .50. In this case it is more likely that these counties do not experience severe weather that can test the investments in protection. I experiment by including only counties with some damage over the sample (not listed here) and find that the high-spending coefficients become

[35] Evidence is available on request.

[36] This estimate is significant at the 6.9% level of significance.

more negative without changing in significance.

5.2.4 Estimates of County vs Federal Spending

HMGP funding becomes available after a presidential disaster declaration and county-funded natural resources spending depends on local budget priorities. In addition to the municipality, HMGP projects are reviewed by the state and the regional FEMA office, and have to meet eligibility criteria (Fraser et al., 2003).[37] The extensive review and emphasis on effectiveness suggests that the HMGP projects are expected to reduce losses. [38] On the other hand, locally funded projects may focus on providing benefits to groups with political influence (Neumayer et al., 2014) rather than directly target weather risk, since citizens pay less attention to pre-disaster prevention (Gasper and Reeves, 2011).

Table 6 lists estimates for the short-term impact. High federal spending has a similar impact across each of the three specifications: it reduces losses by about 0.46% (0.8 BCR).[39] High county spending reduces losses between 0.3% and 0.66%, with the most comprehensive peer groups specification estimating the highest impact. The impact of medium spending by either components is limited. Estimates of the federal spending BCR from Columns (4) and (5), which use continuous measures, suggest that it is slightly under 1. The BCR of county spending is between 1.8 and 4.2, with the second estimate being highly statistically significant. Locally-funded adaptation appears to focus on highly effective projects that can yield robust returns under a variety of scenarios (Hallegatte, 2009). The high estimate is consistent with findings that municipalities are in early planning stages (Woodruff and Stults, 2016) and that officials are incentivized to under-invest in protection because they only reap benefits in the unlikely event of a severe disaster (Neumayer et al., 2014).

Table 7 examines the medium term impact of both components. The indicator-based

[37]Furthermore, 25% of HMGP has to be financed with local funds.

[38]A substantial review of individual projects shows that the average BCR is between 4 and 6 (Mechler, 2016; MMC, 2005, 2017; Rose et al., 2007). Reviews of total county HMGP spending shows BCR that are smaller (Davlasheridze et al., 2017) or higher (Healy and Malhotra, 2009).

[39]Average federal spending at high-federal-spending counties is 0.57%.

specifications in columns (1)-(3) provide a slightly different picture than the continuous-measure-based specifications in (4) and (5). Medium federally-funded spending reduces cumulative losses over the next 5 to 20 years by close to 1%, with the effect being marginally significant in Columns (2) and (3). High federal spending reduces 1.3% of cumulative losses in Column (2) and only 0.1% in Column (3). The high county-funded spending reduces cumulative losses by 1.2% (not statistically significant) in Column (3). Overall, the estimates in column (3) suggest that high county spending and medium federal spending are highly effective at reducing losses.

Columns (4)-(6) of Table 5 examine how the role of each component varies by county risk. In high-risk counties, where overall spending appeared to have a limited impact, only medium federally-funded spending appears to have a consistent risk-reducing effect. Cumulatively, such spending reduces losses by 6.3%, 5 to 20 years after the implementation (statistically significant at 5.8%). This investment is extremely efficient from economic perspective with a BCR of 57. This is different from the case of medium-risk counties, where high county spending plays a prominent role. The cumulative impact of high county spending is to reduce losses by close to 2% (statistically significant at 4%) up to 20 years after the implementation. This suggest that the BCR of such spending is about 9.

5.3 Discussion

There is substantial evidence that public spending on adaptation to severe weather risk is effective and economically efficient. Considering the benefit-cost ratios of investments, I find significant evidence that $1 of spending reduces losses in the short term, or over the next five years, by $1.13. As investments remain longer in place, they continue to reduce further losses, as discussed in (Kunreuther and Michel-Kerjan, 2012), and $1 of spending is expected to prevent close to $3 in losses over the next 20 years. Despite my completely different empirical design based on longitudinal data, my estimates are surprisingly close to those form simulation-based analyses of individual projects which report average savings of about

\$4-\$6 (Mechler, 2016; MMC, 2005, 2017; Rose et al., 2007). More importantly, my estimated impact includes not only federal programs, subject to extensive effectiveness reviews, but also locally-funded projects which are designed and implemented by municipalities.

Weather risk – a combination of hazard frequency and vulnerability – matters significantly for the effectiveness of adaptation measures. I expected to find that adaptation measures in high-risk counties have lower effectiveness because they may be over-provided (Chambwera et al., 2014) but, instead, found evidence that high-spending counties do not have lower losses than low-spending ones. This suggests that these areas may have multiple vulnerabilities which are not addressed by past investments. It is also possible that other types of adaptation, e.g. private investment, may be more important in these counties, leaving public spending as one but not the only way to reduce losses (Aldrich, 2012). Public investment plays a key role predominantly in medium-risk counties, where \$1 saves close to \$2.5 over the next 20 years. Spending in such counties is not just economically efficient, it also reduces a substantial part of losses. The average cumulative saving is 1.36% which is 1.86 standard deviations of damage.

Finally, I find that both the locally-funded and federal component of spending play an important role in adaptation but they do so in different communities. Currently in the US, there is a lack of clear roles and responsibilities across federal, state, and local agencies GAO (2009). My findings suggest that federal spending is focused in high-risk areas, while local spending is effectively implemented in medium-risk counties. Federal (medium) spending is strongly effective at reducing losses in high-risk counties, with \$57 saved for every \$1 invested. Davlasheridze and Miao (2021) similarly finds that federal spending is more effective in high-risk counties. High county-funded spending plays a more prominent role in medium-risk counties, saving \$9 for each \$1. This is partially expected, since federal funds eligibility depends on historical losses. My results confirm that this rule allocates spending where the return is the highest. It is surprising that locally-funded spending has such a significant impact in the light of criticisms that local governments are reluctant to adopt risk reduction policies (Prater and Lindell, 2000) because of polarization and gridlock (Bierbaum et al., 2013), and most of local adaptation involves non-structural measures (Ford et al., 2011). The importance of self-financed county investments confirms that public spending plays an important protective role as showcased in optimization-based models of adaptation and climate change (Neumann et al., 2015, 2021; Ward et al., 2017).

6 Community Diversity and Public Spending

The under-provision of adaptation spending is widely acknowledged (Pielke et al., 2007). In fact, my empirical design assumes that counties closely matched according to weather risk, economic development, and population, are not likely to implement the same amounts of publicly-financed adaptation. This variation is key for the identification and is attributed to a set of adaptation barriers discussed in the literature on the "adaptation deficit", e.g. see (Moser and Ekstrom, 2010). Here, I provide evidence that diversity in opinion and polarization regarding political priorities can reduce public spending (Leiserowitz, 2006). [40]

Adaptation can target a range of possible objectives which reduce the negative effect of severe weather but rely on different strategies (Adger et al., 2009; Carmin and Dodman, 2013).[41] Conflicting individual and group cultures, values, experiences, and divergent risk perceptions can lead to polarization and gridlock regarding how to protect against severe weather (Verweij et al., 2006; Bierbaum et al., 2013). The inability to identify and agree on goals and criteria of spending can impede the planning phase of adaptation (Moser and Ekstrom, 2010). There is evidence that this is a widespread concern, with the majority of US government officials see defining adaptation goals as extremely challenging (GAO, 2009).

I examine the social determinants underlying the cross-county differences in public spend-

[40] There is significant evidence that fragmented places have lower public goods provision, participation in organized activities, trust, and economic success, and that high-hazard counties attract significant population, making them more diverse. See Alesina and Ferrara (2005) for local impact of diversity, and Fulford et al. (2021); Petkov (2018) for its evolution.

[41] For example, communities may focus on building resilience, which promotes the existing structures and functions of the overall community, or on vulnerability, which focuses on the protection of the most endangered (Adger et al., 2009).

ing, which I exploited in order to identify their effectiveness. I follow the literature on barriers to adaptation and empirically explore the importance of divergent opinions as a driving force behind difference in public spending on adaptation against weather risk. I use data from the Yale Climate Opinion Maps (YCOM) on support for public policy related to climate change, i.e. should public policy be a priority, and examine whether county-level diversity and polarization can explain why some counties invest less. I do not focus on questions about whether climate change is happening because since early 2000s public polls demonstrate the large majorities of American are aware of global warming and believe that it is underway (Leiserowitz, 2006). However, there are significant differences in whether climate-change policy should be a priority, with only about half of the population believing that it is.[42]

6.1 Empirical Strategy

My empirical design focuses on the five-year period after a county experiences losses from severe weather and estimates the difference in public spending as a function of the diversity in local opinions about policy priorities. The empirical strategy centers on the period after a direct impact when future risk is most salient (Gallagher, 2014; Cameron and Shah, 2015) and the municipality can be motivated to take action (Gasper and Reeves, 2011).

I retain the definition of peer groups based on income, population, and risk, and estimate a Difference-in-Difference specification, which compares spending after a direct impact by counties with higher diversity of opinion relative to those which are also impacted but have lower diversity. Given the quasi-experimental setting provided by the peers groups, I only compare counties with similar characteristics in order to minimize spending differences due to other unobservables. To further control for availability of federal funding after disasters, I include the lag of damage over the previous five-year period. I also control for additional factors that are important drivers of the availability of post-disaster funding.

[42] As of the writing, 52% believe that global warming should be a high priority for the next president and Congress. https://climatecommunication.yale.edu/visualizations-data/ycom-us/

I estimate the following model:

$$\begin{aligned}\text{Spending}_{c,t} = &\ \beta 1(\text{HighLoss})_{c,t-5} + \gamma 1(\text{HighLoss})_{c,t-5} 1(\text{HighClimatePriorityDiversity})_{c} \\ &+ \sigma \text{Damage}_{c,t-5} + \eta X_{c,t-5} + \text{PeerGroup}_{c} \times \alpha_t + \alpha_c + \epsilon_{c,t}\end{aligned} \tag{3}$$

$\text{Spending}_{c,t}$ refers to total public spending at county c over the five-year period starting with t, as defined above. t. $1(\text{HighLoss})_{c,t-5}$ is an indicator for above-median loss over the period starting with $t-5$. $1(\text{HighClimatePriorityDiversity})_{c}$ is an indicator for the top quartile of diversity in responses about the priority of climate-change policy. Diversity is based on the HHI index using the proportions responding with low, medium, and high/very-high to the question: "Do you think global warming should be a low, medium, high, or very high priority for the next president and Congress?" from the YCOM survey. The index captures the probability that two randomly-selected residents will have a *different* opinion about policy priority Montalvo and Reynal-Querol (2005). I have a cross-section of responses and my diversity measure does not change over time and does not enter the specification on its own but is reflected in the county FE.[43] The rest of the variables are defined as in the main specification. $X_{c,t-5}$ includes measures for income inequality, racial diversity, proportion of minority population. The sample starts with the 2005 period to accommodate the included lag of losses. I exclude spending on buyouts since they are based on the preferences of individual home-owners, not the community, and those who take the buyout may not remain in the county.

β represents the average county investment in adaptation projects over a five-year period (above its long-term average) for counties with above-median losses during the preceding period. It is estimated relative to the set of counties in the peer group. Counties can apply for HMGP funding after an impact and can supplement with local funding if desired spending is higher or if they prefer the flexibility of less oversight from the state/federal government (Smith et al., 2021). A positive estimate quantifies the average additional investment after

[43] There is a concern that diversity can change over time, especially with the occurrence of severe weather. Howe and Leiserowitz (2013); Konisky et al. (2016) provide evidence that this might no be the case, suggesting that climate-change beliefs are only affected by recent shocks and to a much bigger extent by political ideology.

previous impact by severe weather.[44]

γ estimates the additional investment at counties with higher diversity in preferences about policy priorities. Diversity is related to the concept of ambiguity, which results from divergent and contested perspectives on the justification, severity or wider meanings associated with a perceived threat (Stirling, 2003). With high ambiguity, views differ on the ways to assess and appraise the risks, relevance, and implications of available risk information and on which management actions should be considered (Renn et al., 2011). A negative estimate is consistent with diversity – and the resulting ambiguity, reducing the implemented investment, relative to counties with higher agreement about priorities.

I do not control for the average of belief that climate policy is a high priority and focus on the diversity in beliefs. This follows the literature on barriers of adaptation, e.g. (Moser and Ekstrom, 2010), which suggests that difference in opinion and not the opinion in itself can reduce spending by creating conflict about what the specific objectives of adaptation. In the current setting, counties have access to federal funding after a direct impact and can invest regardless of their opinion about whether climate policy should be a priority. However, diversity in opinion can lead to conflict about *how* to spend, which can reduce or postpone investments.

6.2 Results

Estimates for total spending are provided in Table 8. In addition to focusing on the spending decisions of counties after above-median loss I also look at those with loss in the top quartile. I expect that diversity in policy preference will have a stronger impact because counties with higher agreement are likely to spend more after more destructive events. Columns (1) and (2) explore whether counties that give priority to climate-change policy invest more in the five-year period after disasters. There is some evidence that municipalities that prioritize such policy are likely to invest more after above-median impact but not after a stronger impact.

[44] Note that this estimate is not related to the discussion of reversion to mean above. Here spending and losses are separated across periods.

The former invest 1.35% more, with the estimated coefficient being marginally statistically significant, and the latter invest 1.2% (not statistically significant). The average preference does not appear to play an important role in the amount of investment. The high-priority coefficients are both positive but only marginally significant in column (1).

The estimates in columns (3) and (4) suggest that counties with higher disagreement about policy priorities invest less after a direct impact. Those with lower conflict increase spending by 0.8% to 1.4%, depending on the magnitude of the previous losses. In the period after a direct impact, adaptation expenditures increase to the level I designated as high-spending in the previous section. This spending plays a key role in reducing future losses over the next 20 years. However, this is only realized in municipalities with higher agreement; counties with diversity in preferences are unable to increase spending after a previous impact.

Columns (5) and (6) replace diversity with polarization. This is a variation of the HHI index which captures how close the distribution of preferences is to a bipolar, where the majority faces a large minority (Montalvo and Reynal-Querol, 2005). While high diversity implies that opinions can be evenly split between low, medium, and high policy priority, high polarization is consistent with a close split between any two preferences. The results suggest that this type of split across preferred policy priorities is associated with inability to increase spending after an above-median impact. This clarifies that the spending-reducing effect of diversity in column (3) is due to a division in the preferences of resident across two distinct options. The estimates in column (6) are not statistically significant, suggesting that after stronger impact the population in low-spending counties is split not along two policy preferences but along all three.

Next, I focus on the determination of county-funded spending in medium-risk counties, since this type of investment is most critical in these municipalities. The first two columns of Table 9, show that the average preference for climate policy priority does not influence locally-funded investment in adaptation. However, in columns (3) and (4), diversity has a stronger negative effect, particularly in the five-years after higher-loss events. Counties with significant difference in opinion have 2.5%/3.7% lower investment after above-median/top quartile losses. Similarly to the case above, polarization along two types of priority preferences are an important driver of conflict in municipalities with lower losses, while diversity along all three preferences reduces spending after higher losses.

Finally, I consider the role of diversity for federal-funded investment, the key spending type that enables future protection, in high-risk counties. Table 10 list the coefficient estimates. The average priority preference is not associated with differential spending but diversity leads to lower investment. In Column (5), the average county with lower diversity increases spending by 5.6%. However, this is not the case for municipalities with high diversity of preferences, which are unable to increase investment. Column (5) suggests that this is driven by polarization along two preferences. The diversity matters mostly in counties with an intermediate. In columns (4) and (6), spending increases regardless of preferences.

6.3 Discussion

The literature on adaptation spending points to the affordability (Keating et al., 2014), electorate inattentiveness (Gasper and Reeves, 2011), competing priorities (GAO, 2009), and expected payoff (Neumayer et al., 2014) as reasons for its under-provision. More generally, social and individual factors appear to limit how much is invested (Adger et al., 2009). My results further illustrate how the occurrence of severe weather motivates municipalities to spend on adaptation and the importance of agreement among residents about policy priorities. The experience of above-median or top-quartile losses is associated with increased spending in the years that follow. This appears to be partially explained by the eligibility of exposed counties for federal funding under the HMGP. The additional spending showcases an important way in which affected counties can reduce future losses by utilizing funds that are available to them due to previous impacts. However, I find that not all municipalities are able to reduce risk in this fashion. My results suggest that fractionalization among residents about the priority of climate-change policy can be a limiting factor in adaptation spending.

Total spending is significantly lower in areas with high diversity in policy preferences, and more so when opinions are equally split. This is consistent with the analysis in Moser and Ekstrom (2010) who argue that deeply held values and beliefs can represent an important barrier which cuts across all phases in the process of investment in adaptation. The existing conflict about how funding should be spent reduces how much is ultimately invested.

The mechanism that I have illustrated in this section provides one explanation for why counties may end up with different levels of adaptation spending. It relies on differences in local opinions about the importance of climate change, which can lead to gridlock, reducing the level of investment compared to other counties in the control group, and providing a counterfactual for what losses would have been in counties with lower conflict and higher spending.

7 Extensions and Robustness

This section explores several extensions of the main results and examines their sensitivity to alternative specifications.

Effectiveness of Different Type of HMGP Projects: Table 11 examines the effectiveness of federal spending according to type of projects that were implemented. I group projects into five categories: buyouts, building elevation, retrofitting with wind protection, protection of public infrastructure/utilities, and flood control. I only report the estimated coefficients for spending with a statistically significant effect on losses. Columns (1)-(3), using different peer-group specifications, highlight the importance of flood control, elevations, and infrastructure projects in contributing to weather adaptation. Elevations have the highest cumulative impact, reducing losses by 8.3% over a 20 year period, according to Column (3). Infrastructure investment has the second highest impact, reducing losses by 5.2%, and flood control comes in third with a 3.5% reduction. Elevation projects are also extremely efficient with a BCR of over 200. BCR for infrastructure projects is 12 and for flood control is 11.7. All BCR estimates are higher than those reported in MMC (2019), which suggests that historical savings are actually higher than those determined through simulations of hazards.

Controlling for Lagged Losses: Table 12 adds lagged damage to the specification estimating the medium-term impact of total spending. The coefficient estimates for the lag are consistent with some reversion to mean, which is significantly stronger in the specification without peer groups. This supports the assumption that the quasi-experimental empirical design can limit the effect of reversion. The estimates in Column (2) and (3) are close to the main results, with slight decrease in statistical significance and magnitude. The cumulative impact of high spending in column(3) is -1.4% (statistically significant at 5%), which has a BCR of 2.6.

BCR of Federal Projects and Diversity in Preferences: Table 13 examines the impact of diversity in policy preferences on the effectiveness of implemented HMGP projects. A subset of projects reported by the HMGP list the BCR which was supplied with the application for a grant. I use the empirical design that focuses on community diversity and examine whether there are differences in the choice of project effectiveness as a function of local preferences. Columns (1) and (2) show that counties that see climate policy as a priority implement slightly higher BCR projects only after severe loss events. Considering diversity and polarization in local preferences, there is no consistent evidence that more fractionalized communities choose choose more or less effective projects. This further supports the interpretation that higher disagreement can reduce or delay adaptation investments without directly impacting the effectiveness of the projects that are implemented.

8 Conclusion

The study provides substantial evidence that public spending on adaptation to severe weather risk is effective and economically efficient. My key contribution is in considering county-funded projects which are generally missing from the existing literature on the effectiveness of public spending. The benefits of spending continue to accrue over time – as investments remain longer in place, they continue to reduce further losses preventing close to $3 in losses over the next 20 years per $1 spent. I find that both the locally-funded and federal component of spending play an important role in adaptation but they do so in different communities. Federal spending is focused in high-risk areas, while local spending is effectively implemented in medium-risk counties. This is important for future empirical research because it suggests that medium-risk counties utilize county- and time-specific adaptation measures which need to be taken into account when studying local responses to natural hazards.

I also show that not all counties invest in adaptation, and social factors are, at least in part, responsible (Adger et al., 2009). Fractionalization among residents about the priority of climate-change policy can be a limiting factor in adaptation spending. Total spending is significantly lower in areas with high diversity in policy preferences, and more so when opinions are equally split. Such deeply held values and beliefs can represent an important barrier which cuts across all phases in the process of investment in adaptation. The existing conflict about how funding should be spent reduces how much is ultimately invested.

Data availability statement:

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Tables and Figures

Table 1: Summary Statistics: Losses, Hazard Frequency, Resident Vulnerability

The tables provide counties summary statistics (by risk) for 2000-2020. Damage and its components represent county totals over a five-year period relative to GDP at the start of the period. Number of Hurricanes/Floods is total Presidential Disaster Declarations over a five-year period. All fraction variables are out of the county total. Fraction in 100 Year/Direct Impact/500 Year Zone refer to the fraction of housing in areas with flooding during a 1% per year flood event/1% per year event and are directly exposed to waves/ 0.2% year flood event. Fraction of insured refers to the number of insurance policies. Community Rating Insurance Discount is insurance discount applied to policies according to the community safety rating.

(percentage points)	All Counties			High-Risk Counties		
	Mean	SD	90^{th}	Mean	SD	90^{th}
Damage	0.4834	(1.5457)	1.1458	1.4511	(2.9406)	4.5361
Damage (Flood Insurance)	0.0752	(0.4574)	0.0805	0.29	(0.9635)	0.6253
Damage (FEMA)	0.0773	(0.3451)	0.1182	0.204	(0.638)	0.5098
Damage (SBA)	0.2131	(0.7811)	0.4415	0.6545	(1.4911)	1.991
Damage (Public Assistance)	0.0889	(0.4289)	0.1819	0.2266	(0.8769)	0.4874
Number of Hurricanes	0.6759	(0.9174)	2	0.9198	(1.0081)	2
Number of Floods	0.1087	(0.372)	0	0.1524	(0.4461)	1
Fraction in 100 Year Zone	5.3515	(7.2703)	12.84	10.6229	(10.9114)	26.2737
Fraction in Direct Impact Zone	0.0951	(0.8374)	0.0548	0.3434	(1.7888)	0.4506
Fraction in 500 Year Zone	1.8013	(5.5321)	4.0374	4.5146	(9.0573)	10.9938
Fraction 200 yards from Water	13.3819	(11.5761)	28.669	15.4463	(12.4078)	33.5625
Fraction 1000 yards from Water	55.7509	(28.9026)	94.4874	55.3537	(28.114)	92.237
Fraction Insured (100 year Zone)	28.5715	(28.9896)	80.4329	39.5633	(32.3377)	100
Fraction Insured (Direct Impact Zone)	7.7869	(24.4399)	17.8571	19.8337	(36.4831)	100
Fraction Insured (500 year Zone)	57.3635	(40.3525)	100	57.6329	(39.7835)	100
Community Rating Insurance Discount	2.2594	(5.5003)	10	3.0749	(6.0595)	10
Fraction Below Poverty	15.7433	(6.9514)	24.7583	16.8004	(6.7393)	25.3808
Fraction Structure Value \$750K – \$1M	0.1976	(0.6694)	0.4579	0.265	(1.1425)	0.522
Fraction New Construction	3.0328	(1.6163)	5.0739	3.0525	(1.4594)	4.915
Fraction Structures with 20-49 Units	1.1482	(1.7725)	2.5373	0.9406	(1.2276)	2.2183
Fraction Structures with 50+ Units	1.5855	(3.3694)	4.155	1.3654	(2.3434)	4.3081
Fraction Vacant Structures	13.1169	(7.8915)	22.374	17.4915	(10.5749)	32.1087
Fraction Rural Structures	56.2055	(30.1327)	100	61.1733	(30.9338)	100
Fraction Population 65+ of Age	12.7684	(2.7318)	15.7791	13.4732	(2.8095)	16.9747
N	3616			748		

Table 2: Summary Statistics: Risk-reduction Spending

Risk-reduction Spending refers to the annual average federal and county-funded adaptation spending over a five-year period as a fraction of initial year county GDP. County/Federal Spending represent the components of total spending. Is Medium (High) Spending is an indicator for the top 95th (75th to 95th) percentile of spending *for counties with positive spending*. This is similarly defined for the federal and county spending indicators. Spending if Is High (Medium) Spending is the total spending conditional on High/Medium indicators. This is similarly defined for federal and county conditional spending. Federal Flood Control/Buyouts/Elevation/Wind/Infrastructure/Other are subcategories of HMGP projects for: water-management techniques; acquisition of property; raising of property; retrofitting structures for high wind (safe-rooms); utility, water and sewer systems, road and bridges protective measures; warning systems, generators and other. High-Risk Counties are those in the top two quintiles of county risk.

(percentage points)	All Counties			High-Risk Counties		
	Mean	SD	90^{th}	Mean	SD	90^{th}
Risk-reduction Spending (County and Federal)	0.0566	(0.1744)	0.1169	0.1047	(0.3206)	0.2177
County Spending	0.0269	(0.059)	0.0606	0.0387	(0.0779)	0.0891
Federal Spending	0.0297	(0.1586)	0.0522	0.066	(0.3025)	0.111
Is Medium Spending	20.006	(40.0105)	100	28.3046	(45.0803)	100
Is High Spending	4.994	(21.7854)	0	9.7701	(29.7124)	0
Is Medium Federal Spending	5.1734	(22.1524)	0	8.477	(27.874)	0
Is High Federal Spending	3.439	(18.2256)	0	7.0402	(25.6008)	0
Is Medium County Spending	17.1053	(37.6611)	100	21.8391	(41.3451)	100
Is High County Spending	4.2464	(20.1676)	0	7.7586	(26.7712)	0
Spending if Is Medium Spending	0.0929	(0.0425)	0.157	0.0953	(0.0429)	0.1539
Spending if Is High Spending	0.5452	(0.5749)	1.1004	0.6926	(0.8116)	1.3985
Fed Spending if Is Medium Fed Spending	0.111	(0.0352)	0.1672	0.109	(0.0348)	0.1681
Fed Spending if Is High Fed Spending	0.5703	(0.6407)	1.1073	0.7336	(0.9058)	1.4154
County Spending if Is Medium County Spending	0.0555	(0.0195)	0.0879	0.0563	(0.0196)	0.0894
County Spending if Is High County Spending	0.2211	(0.1811)	0.3506	0.2353	(0.1746)	0.3519
Federal: Flood Control	0.0038	(0.0372)	0	0.0077	(0.0637)	0.0005
Federal: Buyouts	0.0125	(0.0874)	0.0067	0.0279	(0.1502)	0.0276
Federal: Elevation	0.0014	(0.0189)	0	0.005	(0.0369)	0
Federal: Wind	0.0072	(0.0512)	0.0009	0.0125	(0.0689)	0.0088
Federal: Infrastructure	0.003	(0.105)	0	0.0107	(0.2291)	0
Federal: Other Prep	0.0017	(0.01)	0.0008	0.0021	(0.0105)	0.0019
N	3344	NA	NA	696	NA	NA

Table 3: Short-term Effect of Risk-reduction Spending

The estimation equations are variations of: $\text{Damage}_{c,t} = \gamma 1(\text{High Spending})_{c,t-5} + \eta 1(\text{Medium Spending})_{c,t-5} + \sigma \text{PDD}_{c,t\in[-5:-25]} + \beta X_{c,t-5} + \text{PeerGroup}_c \times \alpha_t + \alpha_c + \epsilon_{c,t}$. $\text{Damage}_{c,t}$ is county c's total loss over a five-year period, starting at t. $1(\text{High Spending})_{c,t-5}$ is an indicator variable for counties with top 5% investment in the previous five-year period. $1(\text{Medium Spending})_{c,t-5}$ is an indicator for investment between the 75th and the 95th percentile. $\text{PDD}_{c,t\in[-5:-25]}$ represents the set of distributed lags of the count of presidential disaster declarations related to hurricanes, floods, and severe-storms going back to 25 years prior. $X_{c,t-5}$ includes lagged logs of population, personal income, and employment. The sample includes four five-year periods for each county during 2000-2020. OLS Risk Decile uses the cross-sectional county model to predict expected loss for each period; I take the sample median for each county and split the distribution by state deciles. RF Risk decile s similar as OLS Risk Decile but uses predictions from the Random Forest algorithm. Risk Group uses k-means clustering to allocate counties into 15 groups (MA, MD, NJ use 10 groups) based on RF-predicted loss. Risk-Population-Income Group uses k-means clustering to allocate counties into 20 groups (MA, MD, NJ use 10) based on county population, income per capita, RF-predicted risk. Columns (1)-(5) use indicators, columns (6)-(7) use continuous measures of total spending. Residuals are clustered by county. Notation: *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Damage	(2) Damage	(3) Damage	(4) Damage	(5) Damage	(6) Damage	(7) Damage
High Spending$_{t-5}$	-0.00459**	-0.00509**	-0.00404*	-0.00331**	-0.00621***		
	(0.00190)	(0.00203)	(0.00211)	(0.00143)	(0.00194)		
Medium Spending$_{t-5}$	-0.00100	-0.00113	-0.000454	0.000685	0.000241		
	(0.000962)	(0.00105)	(0.00102)	(0.000671)	(0.000787)		
Spending$_{t-5}$						-0.959***	-1.253***
						(0.300)	(0.386)
Spending$_{t-5}$, sq						12.68***	19.29***
						(4.868)	(6.546)
Hurricane Declarations$_{t-5}$	-0.00128	-0.00155**	-0.00206**	-0.00150**	-0.00173**	-0.00144**	-0.00169**
	(0.00103)	(0.000736)	(0.000889)	(0.000596)	(0.000806)	(0.000599)	(0.000812)
Storm Declarations$_{t-5}$	0.000497	9.49e-05	0.000201	-0.000202	0.000107	-0.000200	9.95e-05
	(0.000532)	(0.000581)	(0.000489)	(0.000376)	(0.000469)	(0.000378)	(0.000470)
Flood Declarations$_{t-5}$	-0.00329***	-0.00324***	-0.00171	-0.00228**	-0.00155	-0.00224**	-0.00153
	(0.000930)	(0.00103)	(0.00119)	(0.000930)	(0.000968)	(0.000914)	(0.000982)
Log Population$_{t-5}$	0.00633	0.00275	0.00163	0.00719	0.00144	0.00741	0.00210
	(0.00714)	(0.00739)	(0.00787)	(0.00459)	(0.00625)	(0.00456)	(0.00627)
Log Income$_{t-5}$	-0.00758	-0.0144***	-0.00646	-0.00704**	-0.0101**	-0.00728**	-0.0101**
	(0.00486)	(0.00551)	(0.00501)	(0.00310)	(0.00456)	(0.00314)	(0.00456)
Log Employment$_{t-5}$	-0.00174	0.00353	-1.05e-05	-0.00157	0.000290	-0.00174	-5.40e-05
	(0.00410)	(0.00458)	(0.00424)	(0.00260)	(0.00372)	(0.00261)	(0.00368)
Observations	3,344	3,252	3,312	3,120	2,944	3,120	2,944
R-squared	0.464	0.573	0.639	0.728	0.674	0.729	0.673
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	-	-	-	-	-	-
State OLS Risk Decile x Year FE	-	Yes	-	-	-	-	-
State RF Risk Decile x Year FE	-	-	Yes	-	-	-	-
State Risk Group x Year FE	-	-	-	Yes	-	Yes	-
State Risk-Population-Income Group x Year FE	-	-	-	-	Yes	-	Yes

Table 4: Medium-term Effect of Risk-reduction Spending

The estimation equations are variations of: $\text{Damage}_{c,t} = \sum_{j=5:15} \gamma_j 1(\text{High Spending})_{c,t-j} + \eta_j 1(\text{Medium Spending})_{c,t-j} + \sigma \text{PDD}_{c,t\in[-5:-25]} + \beta X_{c,t-1} + \text{PeerGroup}_c \times \alpha_t + \alpha_c + \epsilon_{c,t}$. For variable definitions, please consult the notes for Table 3. The sample includes two five-year periods starting in 2010. Columns (1)-(3) use indicators; columns (4)-(5) use continuous variables (squared terms are not reported but are included in the estimation). Residuals are clustered by county. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Damage	(2) Damage	(3) Damage	(4) Damage	(5) Damage
High Spending$_{t-5}$	-0.00395	-0.000704	-0.00428**		
	(0.00348)	(0.00189)	(0.00216)		
High Spending$_{t-10}$	-0.00539	-0.00447*	-0.00615*		
	(0.00349)	(0.00235)	(0.00349)		
High Spending$_{t-15}$	-0.00253	-0.00682***	-0.00561**		
	(0.00353)	(0.00252)	(0.00251)		
Medium Spending$_{t-5}$	-0.000317	0.00170	0.00172		
	(0.00180)	(0.00116)	(0.00143)		
Medium Spending$_{t-10}$	-0.00229	-4.39e-05	-0.000962		
	(0.00169)	(0.00126)	(0.00155)		
Medium Spending$_{t-15}$	-0.00149	-0.00134	-0.00162		
	(0.00246)	(0.00144)	(0.00141)		
Spending$_{t-5}$				-0.630*	-0.738
				(0.335)	(0.516)
Spending$_{t-10}$				-3.203***	-3.874***
				(0.767)	(1.178)
Spending$_{t-15}$				-3.429***	-2.585***
				(0.681)	(0.932)
Hurricane Declarations$_{t-5}$	-0.00306**	-0.00154	-0.000683	-0.00115	-0.000748
	(0.00140)	(0.000957)	(0.00107)	(0.000944)	(0.00106)
Storm Declarations$_{t-5}$	-0.00295**	-0.00174**	-0.000484	-0.00223***	-0.000833
	(0.00142)	(0.000865)	(0.00114)	(0.000846)	(0.00113)
Flood Declarations$_{t-5}$	-0.00133	-0.00472***	-0.00297*	-0.00499***	-0.00294*
	(0.00212)	(0.00145)	(0.00167)	(0.00132)	(0.00176)
Log Population$_{t-5}$	0.0212	0.00456	-0.00472	0.00447	-0.00708
	(0.0201)	(0.0135)	(0.0173)	(0.0132)	(0.0169)
Log Income$_{t-5}$	-0.0312***	-0.0135**	-0.0223***	-0.0134**	-0.0205**
	(0.0116)	(0.00656)	(0.00818)	(0.00650)	(0.00816)
Log Employment$_{t-5}$	0.00650	0.0102	0.0179*	0.00826	0.0195**
	(0.0114)	(0.00857)	(0.00955)	(0.00838)	(0.00947)
Observations	1,672	1,560	1,472	1,560	1,472
R-squared	0.660	0.808	0.776	0.817	0.787
County FE	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	-	-	-	-
State Risk Group x Year FE	-	Yes	-	Yes	-
State Risk-Population-Income Group x Year FE	-	-	Yes	-	Yes

Table 5: County Risk and Medium-term Effect of Risk-reduction Spending

The table provides a variation of the specification from column (3) of Table 4, separating the sample by county RF-predicted risk. High/Medium/Low risk refer to the top 80th/40th-80th/bottom 40th percentiles. The estimation equation is: $\text{Damage}_{c,t} = \sum_{j=5:15} \gamma_j 1(\text{High Spending})_{c,t-j} + \eta_j 1(\text{Medium Spending})_{c,t-j} + \sigma \text{PDD}_{c,t\in[-5:-25]} + \beta X_{c,t-1} + \text{PeerGroup}_c \times \alpha_t + \alpha_c + \epsilon_{c,t}$. For variable definitions, please consult the notes for Table 3. The sample includes two five-year periods starting in 2010. Columns (1)-(3) use indicators for total spending; columns (4)-(6) use indicators for county/federal spending. Residuals are clustered by county. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Damage	(2) Damage	(3) Damage	(4) Damage	(5) Damage	(6) Damage
High Spending$_{t-5}$	-0.0175	-0.00155	-0.00260**			
	(0.0110)	(0.00219)	(0.00122)			
High Spending$_{t-10}$	0.00175	-0.00639**	-0.00156			
	(0.0106)	(0.00318)	(0.00117)			
High Spending$_{t-15}$	-0.000741	-0.00563*	-0.000508			
	(0.0128)	(0.00309)	(0.00116)			
Medium Spending$_{t-5}$	-0.0128*	0.00265*	-0.00106			
	(0.00759)	(0.00146)	(0.000910)			
Medium Spending$_{t-10}$	-0.00888	0.000252	-0.00174*			
	(0.00901)	(0.00134)	(0.00103)			
Medium Spending$_{t-15}$	-0.000797	-0.00197*	5.53e-05			
	(0.00681)	(0.00119)	(0.000730)			
High Federal Spending$_{t-5}$				-0.0111	-0.00317	-0.00289*
				(0.00899)	(0.00223)	(0.00150)
High Federal Spending$_{t-10}$				0.00995	-0.00227	-0.00130
				(0.0172)	(0.00338)	(0.00204)
High Federal Spending$_{t-15}$				0.0101	-0.00447*	0.000208
				(0.0160)	(0.00245)	(0.00242)
High County Spending$_{t-5}$				-0.00548	-0.000216	0.00184
				(0.0167)	(0.00263)	(0.00158)
High County Spending$_{t-10}$				-0.00221	-0.00684*	0.000683
				(0.0177)	(0.00398)	(0.00219)
High County Spending$_{t-15}$				-0.0199*	-0.0128***	0.000131
				(0.0116)	(0.00426)	(0.00165)
Medium Federal Spending$_{t-5}$				-0.0244*	0.00249	-0.00123
				(0.0132)	(0.00234)	(0.00145)
Medium Federal Spending$_{t-10}$				-0.0155*	-0.00637	-0.000784
				(0.00922)	(0.00420)	(0.00161)
Medium Federal Spending$_{t-15}$				-0.0228	-0.00407	0.000684
				(0.0208)	(0.00383)	(0.000993)
Medium County Spending$_{t-5}$				0.0137	0.00122	-0.00148
				(0.0132)	(0.00181)	(0.000909)
Medium County Spending$_{t-10}$				-5.70e-05	-0.000438	-0.00212
				(0.0128)	(0.00161)	(0.00138)
Medium County Spending$_{t-15}$				0.00176	-0.00178	-0.000597
				(0.00616)	(0.00119)	(0.000726)
Observations	246	538	556	246	538	556
R-squared	0.820	0.821	0.772	0.851	0.843	0.777
County Risk Sample	High	Medium	Low	High	Medium	Low
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State Risk-Population-Income Group x Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Short-term Effectiveness of Count and Federal Spending

The estimation equations are variations of: $\text{Damage}_{c,t} = \gamma 1(\text{High Spending})_{c,t-5} + \eta 1(\text{Medium Spending})_{c,t-5} + \sigma \text{PDD}_{c,t\in[-5:-25]} + \beta X_{c,t-5} + \text{PeerGroup}_c \times \alpha_t + \alpha_c + \epsilon_{c,t}$. $\text{Damage}_{c,t}$ is county c's total loss over a five-year period, starting at t. Spending indicators refer to High/Medium County/Federally-funded spending, which are defined as the top 95th/75th-95th percentiles. The rest of the variables are defined as in Table 3, please refer to the notes for more information. The sample includes four five-year periods in 2000-2020. Columns (1)-(3) use indicators for the spending variables, columns (4)-(5) use continuous variables, with included squared terms. Residuals are clustered by county. Notation: *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Damage	(2) Damage	(3) Damage	(4) Damage	(5) Damage
High Federal Spending$_{t-5}$	-0.00472**	-0.00462***	-0.00453**		
	(0.00239)	(0.00166)	(0.00194)		
High County Spending$_{t-5}$	-0.00423*	-0.00313	-0.00661***		
	(0.00248)	(0.00223)	(0.00251)		
Medium Federal Spending$_{t-5}$	0.000695	0.00179	-7.32e-05		
	(0.00202)	(0.00136)	(0.00174)		
Medium County Spending$_{t-5}$	-0.00109	-0.00114	-0.000647		
	(0.00103)	(0.000799)	(0.00109)		
Federal Spending$_{t-5}$				-0.934***	-0.957**
				(0.338)	(0.379)
County Spending$_{t-5}$				-1.811	-4.239***
				(1.302)	(1.579)
Federal Spending$_{t-5}$, sq				13.43**	14.39**
				(5.451)	(6.406)
County Spending$_{t-5}$, sq				55.95	195.3**
				(80.33)	(94.88)
Hurricane Declarations$_{t-5}$	-0.00130	-0.00154***	-0.00166**	-0.00144**	-0.00168**
	(0.00104)	(0.000586)	(0.000802)	(0.000600)	(0.000816)
Storm Declarations$_{t-5}$	0.000484	-0.000239	5.93e-05	-0.000203	4.98e-05
	(0.000534)	(0.000372)	(0.000462)	(0.000375)	(0.000460)
Flood Declarations$_{t-5}$	-0.00315***	-0.00206**	-0.00166*	-0.00221**	-0.00170*
	(0.000896)	(0.000854)	(0.000937)	(0.000900)	(0.000974)
Log Population$_{t-5}$	0.00606	0.00687	0.000551	0.00741	0.00147
	(0.00713)	(0.00445)	(0.00618)	(0.00456)	(0.00634)
Log Income$_{t-5}$	-0.00734	-0.00709**	-0.00946**	-0.00727**	-0.00938**
	(0.00483)	(0.00310)	(0.00443)	(0.00316)	(0.00451)
Log Employment$_{t-5}$	-0.00160	-0.00123	0.000330	-0.00181	-0.000350
	(0.00412)	(0.00252)	(0.00371)	(0.00260)	(0.00384)
Observations	3,344	3,120	2,944	3,120	2,944
R-squared	0.465	0.730	0.674	0.729	0.675
County FE	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	-	-	-	-
State Risk Group x Year FE	-	Yes	-	Yes	-
State Risk-Population-Income Group x Year FE	-	-	Yes	-	Yes

Table 7: Medium-term Effectiveness of Count and Federal Spending

The estimation equations are variations of: $\text{Damage}_{c,t} = \sum_{j=5:15} \gamma_j 1(\text{High Spending})_{c,t-j} + \eta_j 1(\text{Medium Spending})_{c,t-j} + \sigma \text{PDD}_{c,t\in[-5:-25]} + \beta X_{c,t-1} + \text{PeerGroup}_c \times \alpha_t + \alpha_c + \epsilon_{c,t}$. Spending indicators refer to High/Medium County/Federally-funded spending, which are defined as the top 95th/75th-95th percentiles. For additional variable definitions, please consult the notes for Table 3. The sample includes two five-year periods starting in 2010. Columns (1)-(3) use indicators; columns (4)-(5) use continuous variables (squared terms are not reported but are included in the estimation). *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Damage	(2) Damage	(3) Damage	(4) Damage	(5) Damage
High Federal Spending$_{t-5}$	-0.00427	-0.00397*	-0.00340		
	(0.00360)	(0.00223)	(0.00246)		
High Federal Spending$_{t-10}$	-0.00345	-0.00526	0.000677		
	(0.00418)	(0.00329)	(0.00446)		
High Federal Spending$_{t-15}$	0.00359	-0.00383	0.00150		
	(0.00427)	(0.00253)	(0.00334)		
High County Spending$_{t-5}$	-0.00410	0.00134	-0.000790		
	(0.00515)	(0.00338)	(0.00300)		
High County Spending$_{t-10}$	7.60e-05	0.000838	-0.00198		
	(0.00447)	(0.00348)	(0.00422)		
High County Spending$_{t-15}$	-0.00261	-0.00701*	-0.00931***		
	(0.00402)	(0.00366)	(0.00339)		
Medium Federal Spending$_{t-5}$	0.00301	0.00233	0.00155		
	(0.00419)	(0.00194)	(0.00258)		
Medium Federal Spending$_{t-10}$	-0.00401	-0.00430**	-0.00513		
	(0.00444)	(0.00201)	(0.00328)		
Medium Federal Spending$_{t-15}$	-0.00643*	-0.00735**	-0.00696**		
	(0.00372)	(0.00366)	(0.00319)		
Medium County Spending$_{t-5}$	-0.000305	0.000621	0.00148		
	(0.00195)	(0.00144)	(0.00196)		
Medium County Spending$_{t-10}$	0.00306	-6.24e-05	-0.00137		
	(0.00267)	(0.00143)	(0.00199)		
Medium County Spending$_{t-15}$	0.00223	0.000511	0.000482		
	(0.00167)	(0.00133)	(0.00134)		
Federal Spending$_{t-5}$				-0.667*	-0.518
				(0.375)	(0.520)
County Spending$_{t-5}$				2.346	-1.551
				(1.971)	(2.941)
Federal Spending$_{t-10}$				-3.251***	-3.704***
				(0.838)	(1.259)
County Spending$_{t-10}$				-2.742	-7.338**
				(2.615)	(3.461)
Federal Spending$_{t-15}$				-2.433***	-0.508
				(0.711)	(1.135)
County Spending$_{t-15}$				-4.312**	-4.385
				(2.148)	(2.673)
Observations	1,672	1,560	1,472	1,560	1,472
R-squared	0.667	0.818	0.789	0.826	0.796
County FE	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	-	-	-	-
State Risk Group x Year FE	-	Yes	-	Yes	-
State Risk-Population-Income Group x Year FE	-	-	Yes	-	Yes

Table 8: Risk-reduction Spending and Policy Preference Diversity

The table provides estimates from the following specification: $\text{Spending}_{c,t} = \beta 1(\text{HighLoss})_{c,t-5} + \gamma 1(\text{HighLoss})_{c,t-5} 1(\text{HighClimatePriorityDiversity})_c + \sigma \text{Damage}_{c,t-5} + \eta X_{c,t-5} + \text{PeerGroup}_c \times \alpha_t + \alpha_c + \epsilon_{c,t}$. $\text{Spending}_{c,t}$ refers to total public spending at county c over the five-year period starting with t, as defined above. t. LossQ34_{t-5}/LossQ4_{t-5} is an indicator for above-median/top-quartile loss over the period starting with $t-5$. PriorityQ4 is an indicator for top quartile of the share responding high to the question: "Do you think global warming should be a low, medium, high, or very high priority for the next president and Congress?" from the YCOM survey. PriorityDiversityQ4/PriorityPolarizationQ4 is the top quartile for diversity/polarization in responses to this question. Diversity $= 1 - \sum_i s_i^2$, where s_i are shares responding high, medium, and low Polarization $= 1 - \sum_i (\frac{.5 - s_i}{.5})^2$. Damages_{t-5} is weather-losses over the previous five-year period. Income Inequality_{t-5} is the gini index from the Census, Racial Diversity_{t-5} is the HHI-based race index. The sample includes three five-year periods starting from 2005. Residuals are clustered by county. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Spending	(2) Spending	(3) Spending	(4) Spending	(5) Spending	(6) Spending
LossQ34_{t-5}	0.00101		0.00824*		0.00880*	
	(0.00468)		(0.00455)		(0.00464)	
LossQ4_{t-5}		0.00344		0.0140**		0.0102
		(0.00497)		(0.00594)		(0.00717)
LossQ34_{t-5} x PriorityQ4	0.0135*					
	(0.00767)					
LossQ4_{t-5} x PriorityQ4		0.0122				
		(0.0136)				
LossQ34_{t-5} x PriorityDiversityQ4			-0.0155*			
			(0.00790)			
LossQ4_{t-5} x PriorityDiversityQ4				-0.0282**		
				(0.0127)		
LossQ34_{t-5} x PriorityPolarizationQ4					-0.0161**	
					(0.00717)	
LossQ4_{t-5} x PriorityPolarizationQ4						-0.0133
						(0.00914)
Damage_{t-5}	0.643	0.552	0.635	0.559	0.637	0.567
	(0.392)	(0.436)	(0.389)	(0.418)	(0.390)	(0.425)
Income Inequality_{t-5}	0.148	0.146	0.161	0.153	0.158	0.148
	(0.173)	(0.174)	(0.172)	(0.172)	(0.173)	(0.175)
Racial Diversity_{t-5}	-0.147	-0.154	-0.139	-0.141	-0.139	-0.152
	(0.173)	(0.174)	(0.171)	(0.169)	(0.172)	(0.174)
Fraction Native American_{t-5}	0.590	0.426	0.577	0.403	0.560	0.482
	(2.165)	(2.198)	(2.159)	(2.105)	(2.155)	(2.167)
Fraction African American_{t-5}	0.0175	0.0357	0.0158	0.0361	0.0155	0.0359
	(0.131)	(0.132)	(0.131)	(0.130)	(0.131)	(0.130)
Log Population_{t-5}	-0.0246	-0.0275	-0.0232	-0.0256	-0.0235	-0.0255
	(0.0710)	(0.0719)	(0.0708)	(0.0717)	(0.0708)	(0.0715)
Log Income_{t-5}	-0.0265	-0.0282	-0.0248	-0.0266	-0.0251	-0.0273
	(0.0372)	(0.0374)	(0.0374)	(0.0378)	(0.0374)	(0.0373)
Log Employment_{t-5}	0.0439	0.0436	0.0440	0.0445	0.0448	0.0438
	(0.0620)	(0.0620)	(0.0614)	(0.0614)	(0.0615)	(0.0616)
Observations	2,204	2,204	2,204	2,204	2,204	2,204
R-squared	0.802	0.802	0.803	0.803	0.803	0.802
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State Risk-Pop-Income Group x Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: County Risk-reduction Spending and Policy Preference Diversity

The table provides estimates from the following specification: $\text{Spending}_{c,t} = \beta 1(\text{HighLoss})_{c,t-5} + \gamma 1(\text{HighLoss})_{c,t-5} 1(\text{HighClimatePriorityDiversity})_c + \sigma \text{Damage}_{c,t-5} + \eta X_{c,t-5} + \text{PeerGroup}_c \times \alpha_t + \alpha_c + \epsilon_{c,t}$. CntySpend refers to county-funded risk-reduction spending. For additional information about variable definions, please refer to Table 8. The sample includes three five-year periods starting from 2005. Residuals are clustered by county. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) CntySpend	(2) CntySpend	(3) CntySpend	(4) CntySpend	(5) CntySpend	(6) CntySpend
LossQ34$_{t-5}$	-0.0109		-0.00415		-0.00345	
	(0.0110)		(0.00637)		(0.00626)	
LossQ4$_{t-5}$		-0.0118		-0.00232		-0.00922
		(0.00776)		(0.00617)		(0.00958)
LossQ34$_{t-5}$ x PriorityQ4	0.00425					
	(0.00807)					
LossQ4$_{t-5}$ x PriorityQ4		-0.0109				
		(0.00852)				
LossQ34$_{t-5}$ x PriorityDiversityQ4			-0.0246*			
			(0.0145)			
LossQ4$_{t-5}$ x PriorityDiversityQ4				-0.0368**		
				(0.0182)		
LossQ34$_{t-5}$ x PriorityPolarizationQ4					-0.0233*	
					(0.0129)	
LossQ4$_{t-5}$ x PriorityPolarizationQ4						-0.0131
						(0.00817)
Damage$_{t-5}$	1.302	1.584*	1.279	1.440*	1.299	1.517*
	(0.799)	(0.919)	(0.782)	(0.850)	(0.792)	(0.904)
Income Inequality$_{t-5}$	-0.0558	-0.0539	-0.0353	-0.0692	-0.0453	-0.0642
	(0.109)	(0.107)	(0.104)	(0.111)	(0.106)	(0.107)
Racial Diversity$_{t-5}$	-0.327	-0.335	-0.313	-0.324	-0.323	-0.338
	(0.338)	(0.345)	(0.326)	(0.334)	(0.331)	(0.341)
Fraction Native American$_{t-5}$	2.505	2.682	2.530	2.213	2.532	2.465
	(2.219)	(2.279)	(2.186)	(2.040)	(2.185)	(2.227)
Fraction African American$_{t-5}$	-0.301	-0.285	-0.289	-0.284	-0.283	-0.288
	(0.238)	(0.244)	(0.232)	(0.235)	(0.230)	(0.242)
Log Population$_{t-5}$	-0.0394	-0.0362	-0.0291	-0.0364	-0.0339	-0.0366
	(0.0470)	(0.0460)	(0.0463)	(0.0463)	(0.0469)	(0.0460)
Log Income$_{t-5}$	-0.0244	-0.0180	-0.0209	-0.0180	-0.0213	-0.0203
	(0.0229)	(0.0233)	(0.0256)	(0.0250)	(0.0252)	(0.0234)
Log Employment$_{t-5}$	0.0335	0.0290	0.0379	0.0348	0.0415	0.0332
	(0.0652)	(0.0676)	(0.0647)	(0.0655)	(0.0648)	(0.0667)
Observations	805	805	805	805	805	805
R-squared	0.783	0.784	0.785	0.789	0.785	0.784
County Risk Sample	Medium	Medium	Medium	Medium	Medium	Medium
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State Risk-Pop-Income Group x Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Federal Risk-reduction Spending and Policy Preference Diversity

The table provides estimates from the following specification: $\text{Spending}_{c,t} = \beta 1(\text{HighLoss})_{c,t-5} + \gamma 1(\text{HighLoss})_{c,t-5} 1(\text{HighClimatePriorityDiversity})_c + \sigma \text{Damage}_{c,t-5} + \eta X_{c,t-5} + \text{PeerGroup}_c \times \alpha_t + \alpha_c + \epsilon_{c,t}$. FedSpend refers to federally-funded risk-reduction spending. For additional information about variable definions, please refer to Table 8. The sample includes three five-year periods starting from 2005. Residuals are clustered by county. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) FedSpend	(2) FedSpend	(3) FedSpend	(4) FedSpend	(5) FedSpend	(6) FedSpend
LossQ34$_{t-5}$	0.0312		0.0559**		0.0559**	
	(0.0204)		(0.0240)		(0.0240)	
LossQ4$_{t-5}$		0.0219		0.0284**		0.0283**
		(0.0138)		(0.0128)		(0.0128)
LossQ34$_{t-5}$ x PriorityQ4	0.00610					
	(0.0178)					
LossQ4$_{t-5}$ x PriorityQ4		-0.00697				
		(0.0262)				
LossQ34$_{t-5}$ x PriorityDiversityQ4			-0.0784*			
			(0.0449)			
LossQ4$_{t-5}$ x PriorityDiversityQ4				-0.0413		
				(0.0344)		
LossQ34$_{t-5}$ x PriorityPolarizationQ4					-0.0784*	
					(0.0449)	
LossQ4$_{t-5}$ x PriorityPolarizationQ4						-0.0387
						(0.0342)
Damage$_{t-5}$	0.110	7.15e-05	0.125	0.0673	0.125	0.0645
	(0.369)	(0.433)	(0.369)	(0.450)	(0.369)	(0.451)
Income Inequality$_{t-5}$	-0.0787	-0.0326	-0.0410	0.0765	-0.0410	0.0684
	(0.455)	(0.439)	(0.463)	(0.485)	(0.463)	(0.485)
Racial Diversity$_{t-5}$	0.0672	-0.0574	0.197	-0.0152	0.197	-0.0189
	(0.566)	(0.587)	(0.584)	(0.604)	(0.584)	(0.604)
Fraction Native American$_{t-5}$	-15.55	-15.29	-16.04	-14.65	-16.04	-14.49
	(12.83)	(12.85)	(12.90)	(13.08)	(12.90)	(13.16)
Fraction African American$_{t-5}$	-1.141	-0.876	-1.124	-0.777	-1.124	-0.781
	(1.059)	(1.010)	(1.046)	(0.994)	(1.046)	(0.995)
Log Population$_{t-5}$	-0.256	-0.194	-0.294	-0.168	-0.294	-0.167
	(0.329)	(0.330)	(0.328)	(0.335)	(0.328)	(0.336)
Log Income$_{t-5}$	0.0488	0.0812	0.0511	0.0649	0.0511	0.0631
	(0.212)	(0.214)	(0.206)	(0.216)	(0.206)	(0.217)
Log Employment$_{t-5}$	-0.201	-0.227	-0.203	-0.227	-0.203	-0.226
	(0.139)	(0.142)	(0.138)	(0.141)	(0.138)	(0.141)
Observations	363	363	363	363	363	363
R-squared	0.784	0.783	0.790	0.784	0.790	0.784
County Risk Sample	High	High	High	High	High	High
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State Risk-Pop-Income Group x Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Medium-term Effect of Federal Spending by Project Type

The estimation equations are variations of: $\text{Damage}_{c,t} = \sum_{j=5:15} \gamma_j 1(\text{High Spending})_{c,t-j} + \eta_j 1(\text{Medium Spending})_{c,t-j} + \sigma \text{PDD}_{c,t\in[-5:-25]} + \beta X_{c,t-1} + \text{PeerGroup}_c \times \alpha_t + \alpha_c + \epsilon_{c,t}$. Spending indicators refer to High/Medium County/Federally-funded spending, which are defined as the top 95th/75th-95th percentiles. Federal spending is divided by the purpose of the HMGP project. Six types of projects are included in the specification, however, I only include statistically significant ones. Federal Flood Control/Buyouts/Elevation/Wind/Infrastructure/Other are subcategories of HMGP projects for: water-management techniques; acquisition of property; raising of property; retrofitting structures for high wind (safe-rooms); utility, water and sewer systems, road and bridges protective measures; warning systems, generators and other. For additional variable definitions, please consult the notes for Table 3. The sample includes two five-year periods starting in 2010. Columns (1)-(3) use indicators; columns (4)-(5) use continuous variables (squared terms are not reported but are included in the estimation). *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Damage	Damage	Damage	Damage	Damage
High Fed Spend: Flood Control$_{t-5}$	-0.0106*	-0.00510	-0.00580		
	(0.00557)	(0.00409)	(0.00701)		
High Fed Spend: Flood Control$_{t-10}$	-0.0107**	-0.00656	-0.0169*		
	(0.00439)	(0.00651)	(0.00915)		
High Fed Spend: Flood Control$_{t-15}$	-0.00673	-0.0253*	-0.0122		
	(0.00906)	(0.0146)	(0.00894)		
High Fed Spend: Elevation$_{t-5}$	0.00106	0.00769	-0.00520		
	(0.00777)	(0.00653)	(0.00758)		
High Fed Spend: Elevation$_{t-10}$	-0.00654	0.0291***	-0.0170		
	(0.0144)	(0.00961)	(0.0161)		
High Fed Spend: Elevation$_{t-15}$	-0.0430**	-0.0251	-0.0608***		
	(0.0182)	(0.0208)	(0.0195)		
High Fed Spend: Infrastructure$_{t-5}$	-0.0185*	-0.0240***	-0.0160*		
	(0.00976)	(0.00742)	(0.00833)		
High Fed Spend: Infrastructure$_{t-10}$	-0.0202***	-0.0280***	-0.0277***		
	(0.00780)	(0.00941)	(0.00819)		
High Fed Spend: Infrastructure$_{t-15}$	-0.00714	-0.0144	-0.00846		
	(0.00728)	(0.00901)	(0.00836)		
Fed Spend: Flood Control$_{t-5}$				-2.310***	-2.312*
				(0.838)	(1.284)
Fed Spend: Flood Control$_{t-10}$				-3.201	-6.531**
				(2.834)	(2.718)
Fed Spend: Flood Control$_{t-15}$				-12.10	-11.99*
				(8.864)	(6.136)
Fed Spend: Elevation$_{t-5}$				0.108	-5.676
				(1.844)	(5.067)
Fed Spend: Elevation$_{t-10}$				11.65***	2.108
				(2.655)	(4.514)
Fed Spend: Elevation$_{t-15}$				0.979	19.99
				(8.129)	(15.14)
Fed Spend: Infrastructure$_{t-5}$				-0.509***	-0.460***
				(0.0847)	(0.0888)
Fed Spend: Infrastructure$_{t-10}$				-3.228	-4.875**
				(3.026)	(1.910)
Fed Spend: Infrastructure$_{t-15}$				7.218	-5.472
				(10.96)	(10.48)
Observations	1,672	1,560	1,472	1,560	1,472
R-squared	0.671	0.829	0.796	0.825	0.800
County FE	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	-	-	-	-
State Risk Group x Year FE	-	Yes	-	Yes	-
State Risk-Population-Income Group x Year FE	-	-	Yes	-	Yes

Table 12: Medium-term Effect of Risk-reduction Spending With Lagged Damage

The estimates replicate Table 4 by including the lag of weather-related damages from the preceding period. The estimation equations are variations of: $\text{Damage}_{c,t} = \sum_{j=5:15} \gamma_j 1(\text{High Spending})_{c,t-j} + \eta_j 1(\text{Medium Spending})_{c,t-j} + \sigma \text{PDD}_{c,t\in[-5:-25]} + \beta X_{c,t-1} + \text{PeerGroup}_c \times \alpha_t + \alpha_c + \epsilon_{c,t}$. For variable definitions, please consult the notes for Table 3. The sample includes two five-year periods starting in 2010. Columns (1)-(3) use indicators; columns (4)-(5) use continuous variables (squared terms are not reported but are included in the estimation). Residuals are clustered by county. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Damage	(2) Damage	(3) Damage	(4) Damage	(5) Damage
High Spending$_{t-5}$	-0.000492	-0.000762	-0.00310		
	(0.00284)	(0.00194)	(0.00200)		
High Spending$_{t-10}$	-0.00883***	-0.00444*	-0.00647*		
	(0.00331)	(0.00234)	(0.00340)		
High Spending$_{t-15}$	-0.00317	-0.00687***	-0.00416*		
	(0.00300)	(0.00257)	(0.00229)		
Medium Spending$_{t-5}$	0.00162	0.00165	0.00203		
	(0.00149)	(0.00112)	(0.00145)		
Medium Spending$_{t-10}$	-0.00311*	-5.03e-05	-0.00125		
	(0.00163)	(0.00126)	(0.00157)		
Medium Spending$_{t-15}$	0.000406	-0.00136	-0.00171		
	(0.00212)	(0.00140)	(0.00135)		
Spending$_{t-5}$				-0.631*	-0.708
				(0.336)	(0.489)
Spending$_{t-10}$				-3.254***	-3.916***
				(0.775)	(1.182)
Spending$_{t-15}$				-3.561***	-2.101**
				(0.709)	(0.896)
Damage$_{t-5}$	-0.448***	0.0182	-0.226***	0.0771	-0.194**
	(0.0935)	(0.0889)	(0.0870)	(0.0852)	(0.0870)
Hurricane Declarations$_{t-5}$	-0.00251**	-0.00156*	-0.00115	-0.00116	-0.00130
	(0.00127)	(0.000939)	(0.00107)	(0.000939)	(0.00109)
Storm Declarations$_{t-5}$	-0.00177	-0.00177**	7.98e-05	-0.00242***	-0.000293
	(0.00116)	(0.000899)	(0.00107)	(0.000890)	(0.00111)
Flood Declarations$_{t-5}$	-0.00236	-0.00474***	-0.00259**	-0.00516***	-0.00246*
	(0.00178)	(0.00148)	(0.00127)	(0.00136)	(0.00148)
Log Population$_{t-5}$	0.0178	0.00439	-0.00362	0.00357	-0.00568
	(0.0180)	(0.0136)	(0.0171)	(0.0135)	(0.0168)
Log Income$_{t-5}$	-0.0350***	-0.0133**	-0.0247***	-0.0124*	-0.0228***
	(0.0104)	(0.00668)	(0.00827)	(0.00661)	(0.00828)
Log Employment$_{t-5}$	0.0137	0.0102	0.0171*	0.00781	0.0189**
	(0.0100)	(0.00861)	(0.00908)	(0.00855)	(0.00907)
Observations	1,672	1,560	1,472	1,560	1,472
R-squared	0.733	0.808	0.788	0.818	0.796
County FE	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	-	-	-	-
State Risk Group x Year FE	-	Yes	-	Yes	-
State Risk-Population-Income Group x Year FE	-	-	Yes	-	Yes

Table 13: BCR of Federal Spending and County Diversity

The estimates replicate the results from Table 8 using a different dependent variable. The table provides estimates from the following specification: $\text{BCR}_{c,t} = \beta 1(\text{HighLoss})_{c,t-5} + \gamma 1(\text{HighLoss})_{c,t-5} 1(\text{HighClimatePriorityDiversity})_c + \sigma \text{Damage}_{c,t-5} + \eta X_{c,t-5} + \text{PeerGroup}_c \times \alpha_t + \alpha_c + \epsilon_{c,t}$. $\text{BCR}_{c,t}$ refers to the average reported benefit-cost ratio of federal projects at county c over the five-year period starting with t, as defined above. t. LossQ34_{t-5}/LossQ4_{t-5} is an indicator for above-median/top-quartile loss over the period starting with $t-5$. PriorityQ4 is an indicator for top quartile of the share responding high to the question: "Do you think global warming should be a low, medium, high, or very high priority for the next president and Congress?" from the YCOM survey. PriorityDiversityQ4/PriorityPolarizationQ4 is the top quartile for diversity/polarization in responses to this question. Diversity $= 1 - \sum_i s_i^2$, where s_i are shares responding high, medium, and low Polarization $= 1 - \sum_i (\frac{.5 - s_i}{.5})^2$. Damages_{t-5} is weather-losses over the previous five-year period. Income Inequality_{t-5} is the gini index from the Census, Racial Diversity_{t-5} is the HHI-based race index. The sample includes three five-year periods starting from 2005. Residuals are clustered by county. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) BCR	(2) BCR	(3) BCR	(4) BCR	(5) BCR	(6) BCR
LossQ34_{t-5}	-0.372		-0.898		-0.921	
	(0.820)		(0.829)		(0.847)	
LossQ4_{t-5}		-1.722*		-1.263		-1.260
		(0.938)		(0.833)		(0.822)
LossQ34_{t-5} x PriorityQ4	0.565					
	(0.880)					
LossQ4_{t-5} x PriorityQ4		1.627**				
		(0.818)				
LossQ34_{t-5} x PriorityDiversityQ4			1.832*			
			(0.994)			
LossQ4_{t-5} x PriorityDiversityQ4				1.408		
				(1.163)		
LossQ34_{t-5} x PriorityPolarizationQ4					1.847*	
					(1.006)	
LossQ4_{t-5} x PriorityPolarizationQ4						1.403
						(1.144)
Damage_{t-5}	-2.002	0.0714	-1.631	1.892	-1.637	1.499
	(6.775)	(8.175)	(6.953)	(8.143)	(6.964)	(7.921)
Income Inequality_{t-5}	-1.189	-2.294	-6.489	-5.818	-6.839	-8.142
	(9.961)	(9.632)	(9.483)	(9.294)	(9.493)	(9.584)
Racial Diversity_{t-5}	-14.09	-16.81	-12.63	-14.06	-12.57	-13.01
	(11.60)	(11.94)	(11.15)	(11.50)	(11.13)	(11.12)
Fraction Native American_{t-5}	-209.7	-203.0	-205.1	-210.8	-209.1	-235.7
	(166.1)	(148.1)	(171.7)	(145.1)	(172.4)	(153.3)
Fraction African American_{t-5}	-11.21	-10.13	-17.94	-15.34	-18.08	-15.12
	(15.13)	(14.49)	(13.90)	(13.79)	(13.92)	(13.53)
Log Population_{t-5}	-3.539	-2.776	-2.458	-3.048	-2.767	-3.385
	(8.188)	(7.138)	(7.715)	(6.987)	(7.737)	(7.003)
Log Income_{t-5}	6.145	7.301	6.552	6.195	6.697	6.289
	(4.525)	(4.989)	(4.378)	(4.625)	(4.412)	(4.636)
Log Employment_{t-5}	-0.854	-1.866	-2.849	-1.293	-2.828	-1.235
	(3.841)	(3.214)	(3.624)	(3.339)	(3.612)	(3.320)
Observations	486	486	486	486	486	486
R-squared	0.882	0.888	0.884	0.885	0.884	0.885
County FE	Yes	Yes	Yes	Yes	Yes	Yes
State Risk-Pop-Income Group x Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Figure 1: Weather-related Losses by: Full Sample, Weather Risk, Individual States

This figure shows the distribution of weather-related losses in the sample. Loss is defined as the total county damage over a five-year period divided by county GDP at the start of the period. In each case continuous losses are clustered into five different categories and the graphs list the lower bound. The top left panel shows the histogram for the entire sample from 2000 to 2020. The top right panel divides counties by their state-specific risk category and plots a histogram for those below and above the state median. The bottom panels provide histograms for each state in the sample.

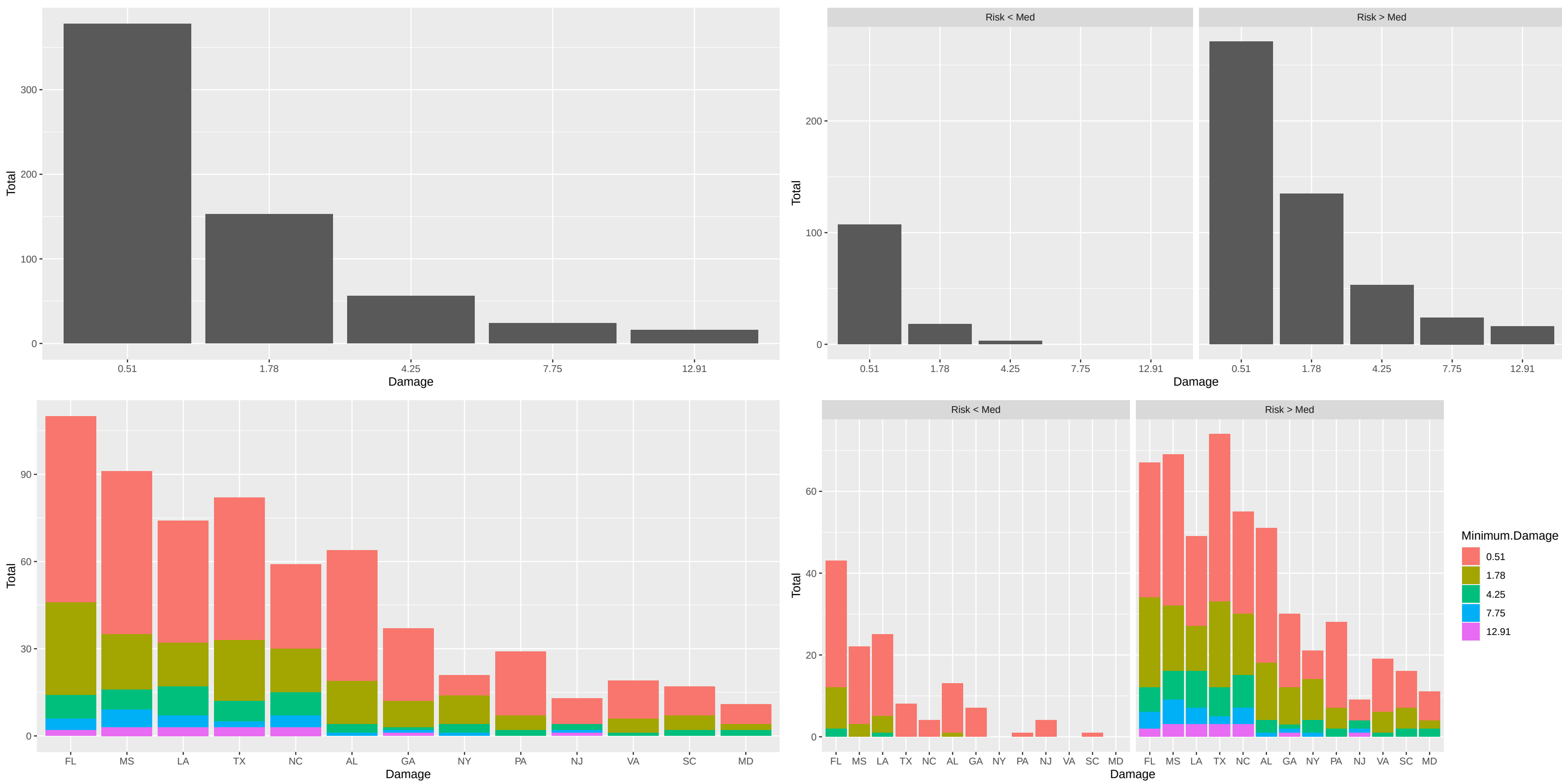


Figure 2: Weather-related Losses: Spatial Distribution over Time and Components

This figure provides the spatial distribution of total loss and its components for each five-year period in the sample. All measures in percentage points. Total damage is defined as the total county damage over a five-year period divided by county GDP at the start of the period. Insured loss is based on flood insurance information from the National Flood Insurance Program. Uninsured Fema Loss comes from losses associated with FEMA's individual and household assistance program. Uninsured SBA loss is based on the reported losses by the SBA disaster loan program. Uninsured Public loss comes from FEMA's public assistance program.

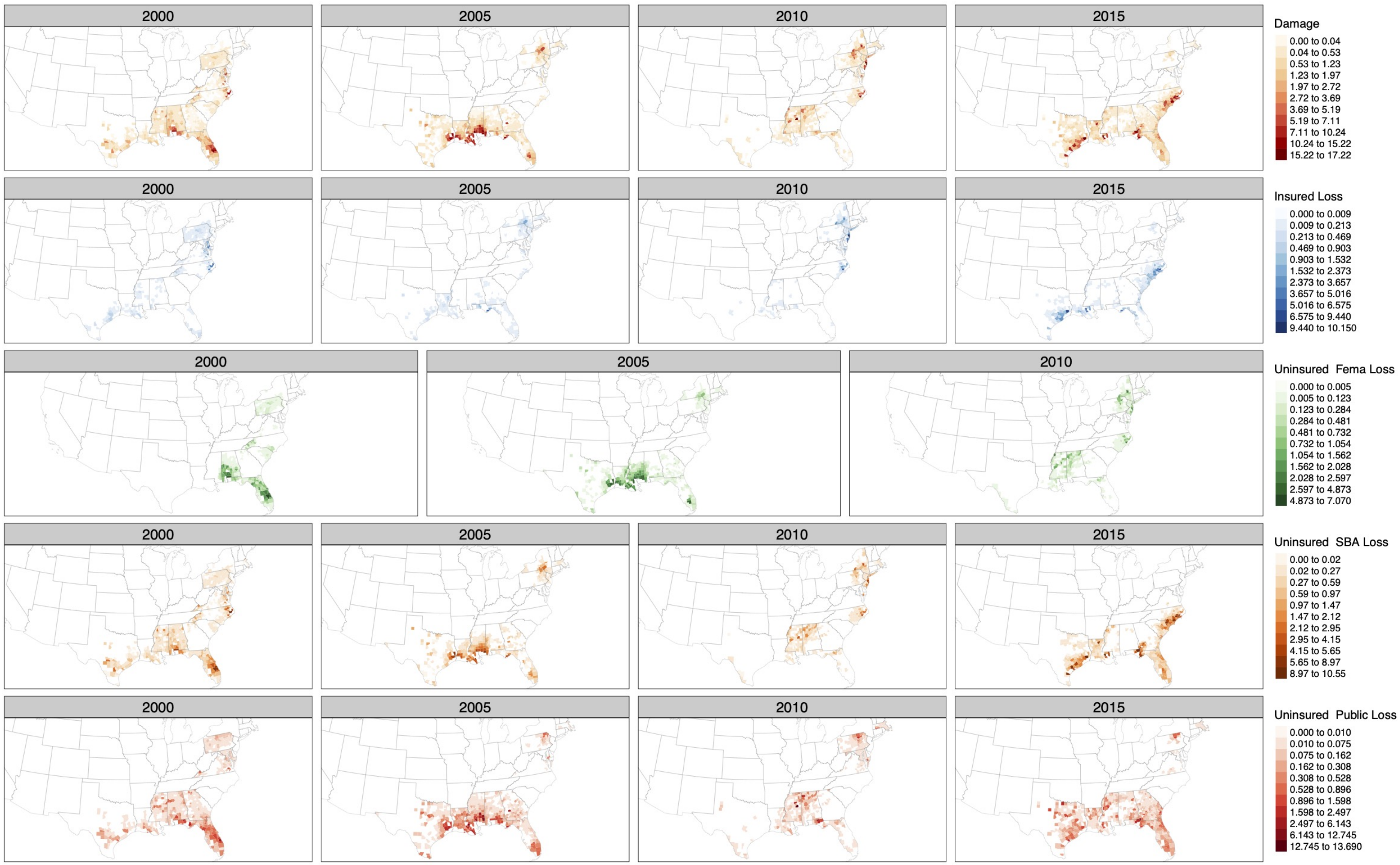


Figure 3: Risk-reduction Spending: Spatial Distribution over Time and Components

This figure provides the spatial distribution of risk-reduction spending and its main components for each five-year period in the sample. All measures in percentage points. Mitigation is defined as the annual average of HMGP projects over a five-year period divided by county GDP at the start of the period. For definition of each component refer to Table 1.

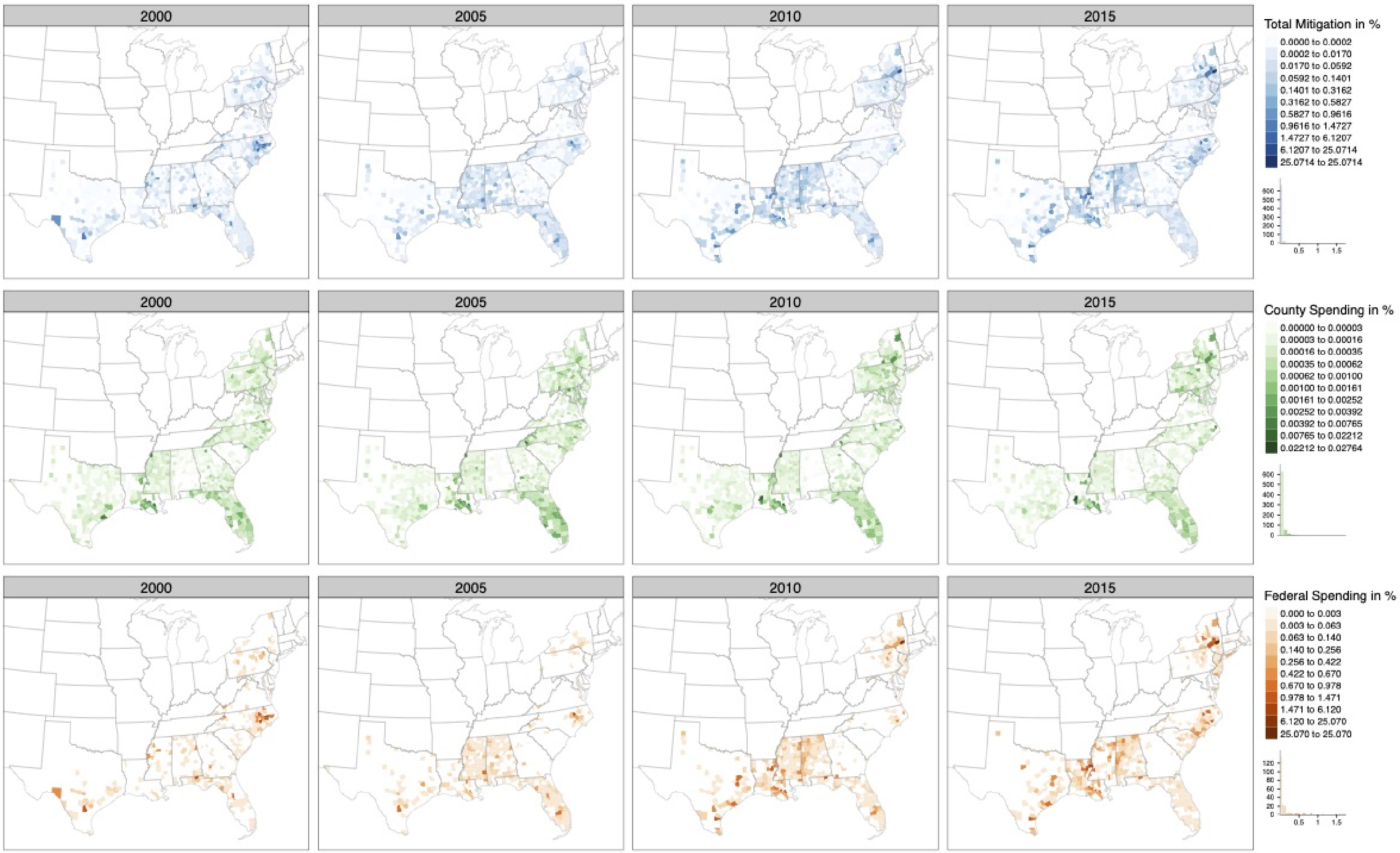


Figure 4: Weather-related Loss: Actual Damage and Random Forest Predictions

This figure compares the spatial distribution of actual loss for each period in the sample and the predictions based on the Random Forest Machine Learning Algorithm. For additional definitions please refer to Figure 2.

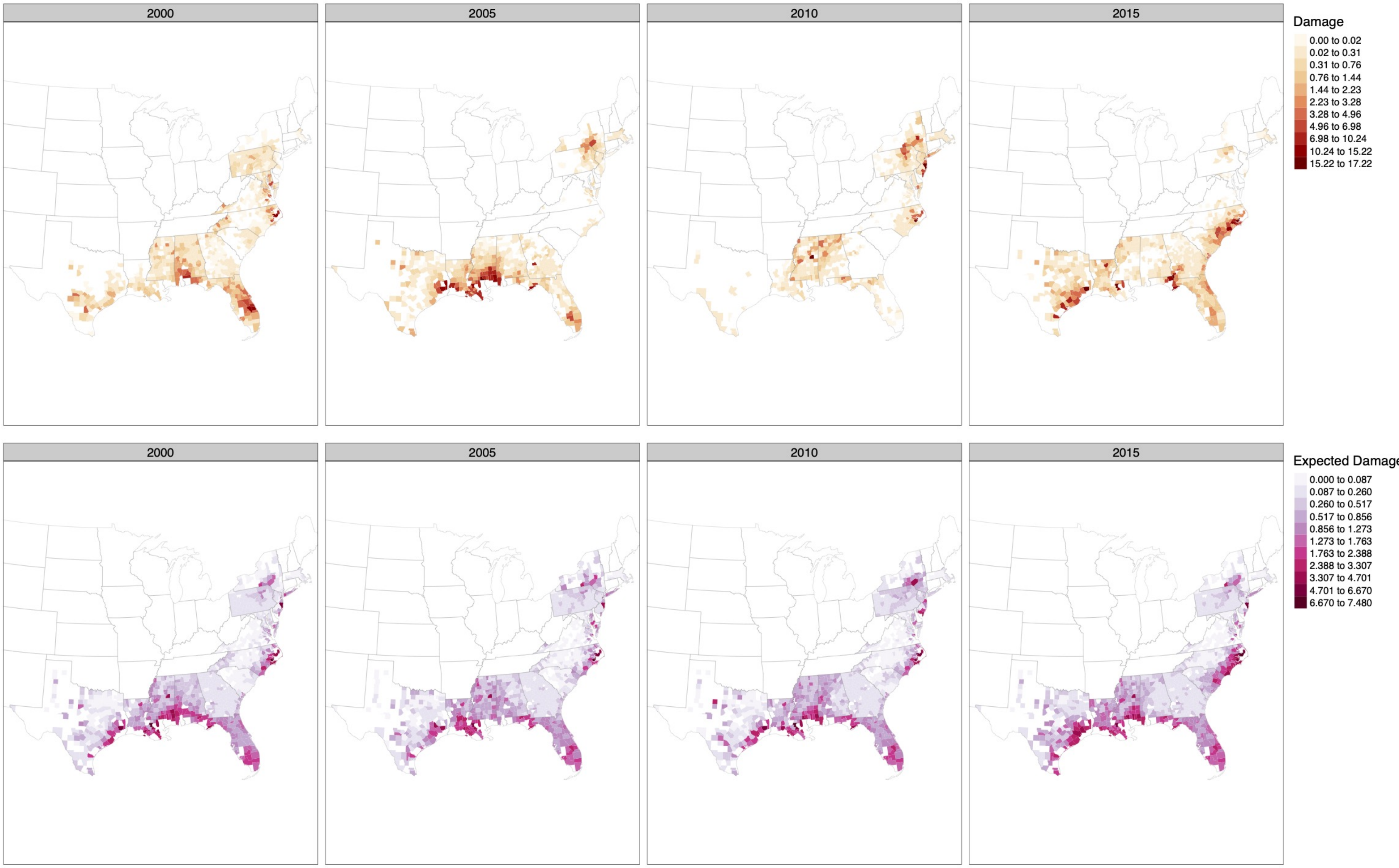


Figure 5: Ranking of Random Forest Predictions

This figure distinguishes county risk based on the quintile (left) and decile (right) of expected losses within each state. Expected losses for each county are the median predicted loss from the Random-Forest Algorithm over the sample.

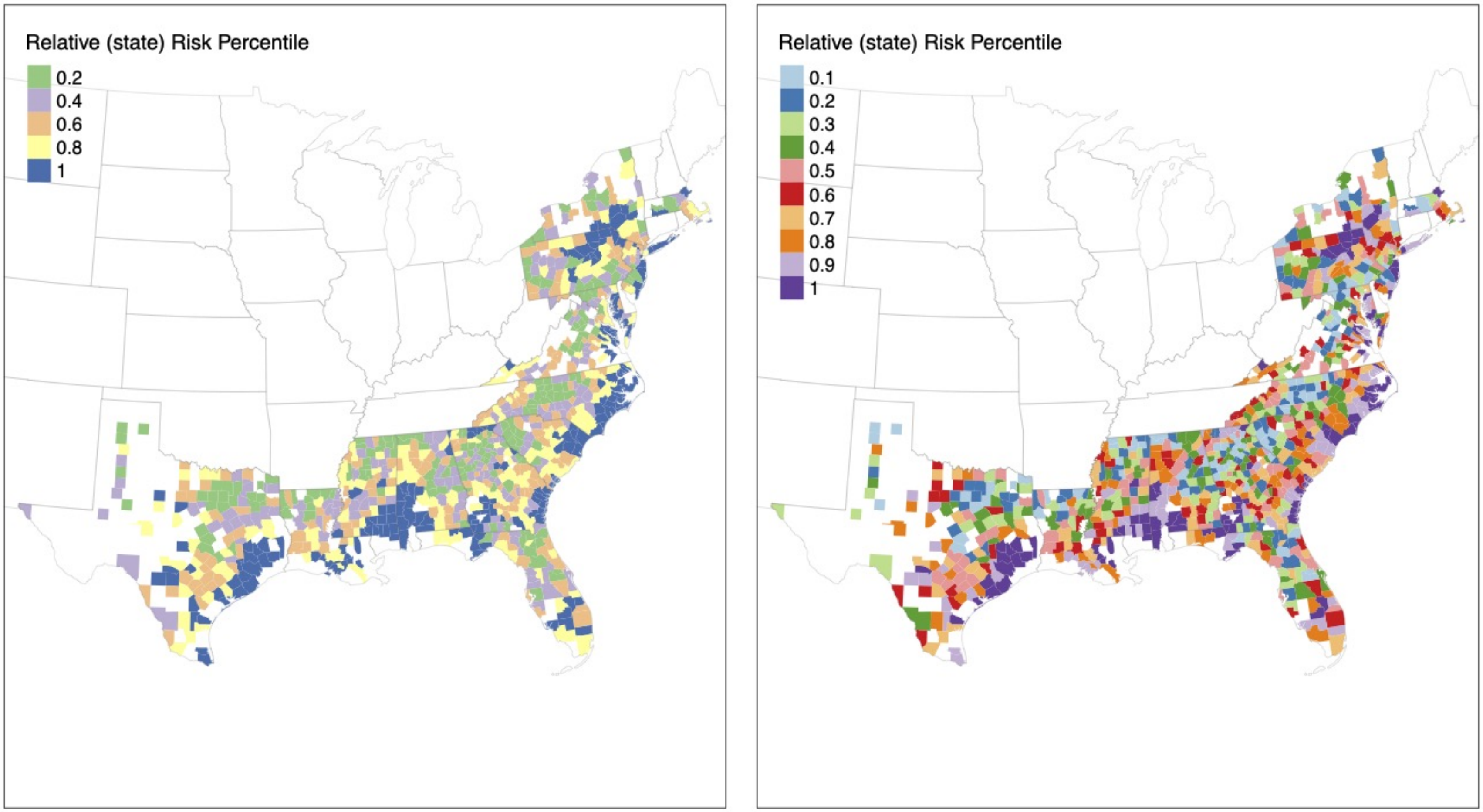


Figure 6: Distribution of Risk-reduction Spending by Predicted Weather Risk

This figure shows the distribution of total risk-reduction spending and components by county risk quintile. Spending is measured as the county average annual over a five-year period as a fraction of the county GDP at the start of the period. Measures are in percentage points.

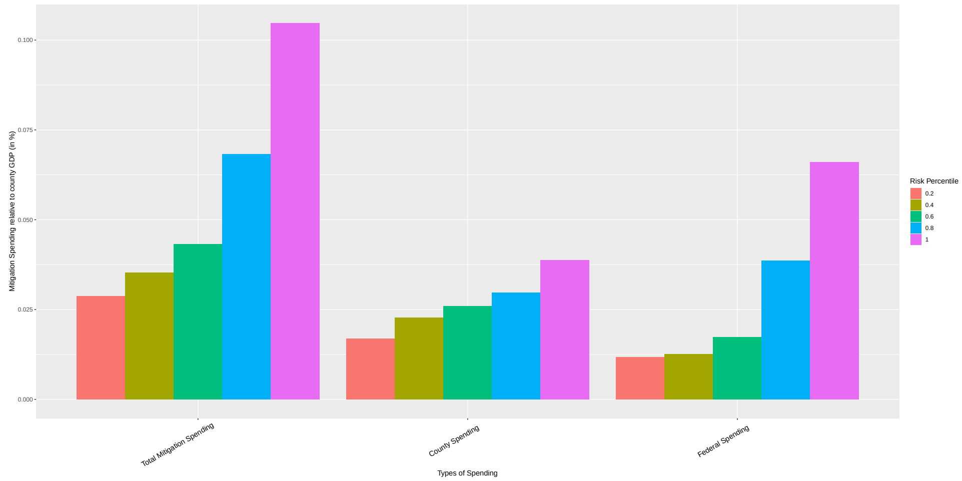
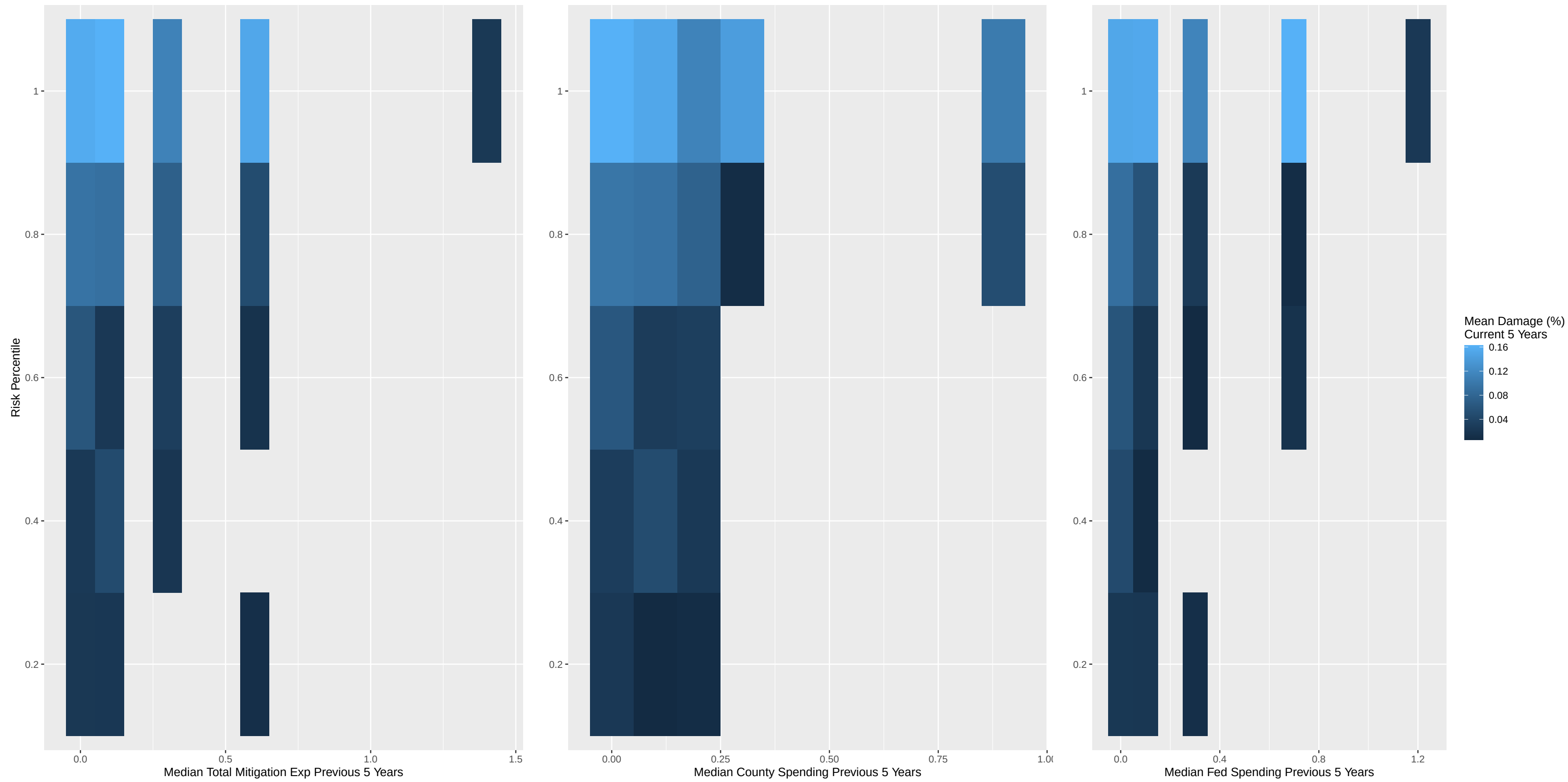


Figure 7: Average Risk-reduction Spending and Weather-related Loss

The figure shows the relationship between median risk-reduction spending over all periods, the risk quintile, and the average loss experienced during the sample. All measures are based on the sample and do not represent model-based estimates.



Appendix (for online publication)

Appendix A: Robustness and Extensions

Table A1: Selected Summary Statistics by State

The table lists a subset of statistics from Table 1 for each of the states included in the sample. n is the number of counties for each state included in the sample.

		Damage	100Y Zone	500Y Zone	Close to Water	Insured (100Y)	Insured (500Y)	Insurance Discount	Poverty	50+ Units	Vacant
AL, n=65	mean	0.5058	3.602	0.7228	12.1957	11.735	46.5374	0.3846	19.1278	0.8098	13.5987
	sd	(1.0781)	(2.6192)	(1.1748)	(9.2247)	(10.5434)	(38.7126)	(1.8238)	(6.6971)	(1.0637)	(4.3322)
FL, n=58	mean	1.2139	11.809	4.3631	21.1053	52.7795	79.4918	12.931	14.1377	2.9825	15.9779
	sd	(2.1755)	(10.6341)	(7.3214)	(16.9152)	(36.2525)	(33.6938)	(8.6807)	(4.6171)	(3.8873)	(7.7833)
GA, n=150	mean	0.176	3.1553	1.0901	16.0868	18.5712	49.143	1.3167	16.6854	0.782	11.9002
	sd	(0.8655)	(3.8433)	(4.1627)	(10.458)	(22.7043)	(45.7639)	(3.8513)	(6.4264)	(1.3616)	(5.9129)
LA, n=46	mean	1.3039	11.3729	4.9498	12.4577	36.3354	48.3835	2.2826	22.8657	0.9331	12.8543
	sd	(2.6353)	(10.6686)	(15.1107)	(10.1762)	(32.8548)	(44.4611)	(4.6408)	(5.9955)	(1.523)	(5.0224)
MA, n=12	mean	0.0641	4.7862	1.634	22.6781	57.1733	69.1223	1.25	9.2416	4.0671	16.1333
	sd	(0.0938)	(3.4832)	(1.0728)	(6.8829)	(18.5342)	(34.5278)	(3.0071)	(3.8416)	(3.2921)	(20.9263)
MD, n=23	mean	0.2584	5.0302	1.2617	17.0152	56.7383	88.393	4.1304	8.668	2.4545	11.1159
	sd	(0.8235)	(8.5893)	(1.4183)	(10.5887)	(28.4935)	(23.4006)	(6.8983)	(4.2369)	(3.5695)	(12.0288)
MS, n=76	mean	0.8904	5.7712	1.7714	4.7785	16.4677	43.4795	1.0526	23.2093	0.6191	11.069
	sd	(2.1876)	(6.7759)	(9.8263)	(6.1851)	(16.0138)	(40.41)	(3.074)	(7.2164)	(1.0239)	(3.757)
NC, n=99	mean	0.5395	4.7466	1.6993	10.4398	32.527	67.0897	2.8283	14.2485	0.6787	14.6787
	sd	(1.9282)	(9.2922)	(2.723)	(9.5179)	(29.8649)	(32.0979)	(5.8315)	(4.2093)	(0.9919)	(9.8919)
NJ, n=21	mean	0.5649	7.7493	2.5322	15.9503	62.9729	65.2797	2.381	8.0845	4.8479	8.5483
	sd	(2.1659)	(10.3033)	(2.3284)	(7.8761)	(24.6986)	(26.4005)	(5.5143)	(3.8851)	(3.3285)	(11.0362)
NY, n=43	mean	0.3831	3.0738	1.4441	11.0057	57.6496	64.7439	0.2326	12.2221	5.1513	12.6881
	sd	(1.1729)	(2.7767)	(1.547)	(5.7409)	(34.6048)	(34.9911)	(1.056)	(4.5829)	(10.0965)	(8.8469)
PA, n=66	mean	0.2402	4.6801	1.6255	11.2483	23.7949	48.7624	0.303	10.838	1.8081	13.7557
	sd	(0.6452)	(4.0935)	(1.9277)	(9.3082)	(14.2943)	(30.9867)	(1.7175)	(3.2959)	(1.5529)	(11.162)
SC, n=45	mean	0.2117	3.574	1.0392	8.1345	34.0082	65.9478	3.1111	17.0133	0.9668	12.9142
	sd	(0.7919)	(5.9654)	(2.9092)	(5.4043)	(33.5157)	(41.2362)	(5.9127)	(5.4439)	(1.2314)	(5.2435)
TX, n=132	mean	0.4174	6.039	1.8721	15.4147	20.8287	58.7729	1.7424	16.4806	2.1759	14.1109
	sd	(1.4877)	(6.8614)	(2.9958)	(15.7841)	(23.9159)	(40.8159)	(5.1536)	(6.8382)	(2.7988)	(6.4362)
VA, n=68	mean	0.1579	4.1009	1.0176	15.9225	21.0765	54.6527	0.6618	11.4346	0.803	12.5036
	sd	(0.5997)	(5.917)	(1.8157)	(8.6488)	(21.1132)	(41.5932)	(2.7036)	(5.1284)	(4.0289)	(6.8175)

Table A2: Summary Statistics: Historical Disaster Declarations

The tables provides summary statistics for lags of presidential disaster declarations for counties in the sample for 2000-2020. Each lag represents the count of disaster declarations over a five-year period. LnHurricane/Ln2Hurricane refer to the number of declarations 5-10/10-15 years prior. Hurricane/Flood/Storm refer to disaster declarations related to hurricanes, flooding, and severe storms.

Variable	Observations	Mean	Std. Dev.	Min	Max
LnHurricane	3344	0.624	0.892	0	5
L2nHurricane	3344	0.532	0.876	0	5
L3nHurricane	3344	0.398	0.760	0	5
L4nHurricane	3344	0.189	0.541	0	5
L5nHurricane	3344	0.054	0.232	0	2
LnFlood	3344	0.114	0.364	0	2
L2nFlood	3344	0.137	0.394	0	3
L3nFlood	3344	0.167	0.427	0	3
L4nFlood	3344	0.184	0.444	0	3
L5nFlood	3344	0.195	0.469	0	3
LnStorm	3344	0.639	0.825	0	7
L2nStorm	3344	0.640	0.825	0	7
L3nStorm	3344	0.502	0.764	0	7
L4nStorm	3344	0.288	0.548	0	4
L5nStorm	3344	0.177	0.460	0	3

Table A3: Weather-related Loss: OLS Estimates of Hazard Frequency and Vulnerability

The table lists estimates from OLS regressions of weather-related loss on four different sets of factors. In each case the sample includes four five-year county observations during 2000-2020. Some coefficients are omitted for legibility. Column (1) includes lags of disaster declarations for hurricanes, floods, and severe storms. For each I include total declarations 5-10/10-15/15-20/20-25/25-30 years prior. Column (2) adds a first set of vulnerability measures based on fractions in flood zones, distance to water, insurance rates, flood-insurance discounts. Column (3) adds a second set of vulnerability measures based on Census characteristics. Column (4) distinguishes all variables in column (3) by the flood zone. Each estimation includes a state fixed effect. For an additional definition of variables please consult Table 1. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) Damage	(2) Damage	(3) Damage	(4) Damage
Hurricanes$_{t-1}$	0.00121**	0.000557	0.000507	0.000459
	(0.000474)	(0.000409)	(0.000406)	(0.000408)
Floods$_{t-1}$	-2.22e-05	-0.000653	-0.000725	-0.000653
	(0.000662)	(0.000690)	(0.000696)	(0.000672)
Storms$_{t-1}$	0.000743**	0.000788**	0.000733**	0.000780**
	(0.000363)	(0.000361)	(0.000352)	(0.000351)
Flood Zone 100Y		0.0403***	0.0412***	0.00933
		(0.00874)	(0.00928)	(0.0585)
Flood Zone 100Y, Direct Impact		0.182***	0.166***	0.579*
		(0.0294)	(0.0284)	(0.343)
Flood Zone 500Y		0.00592	0.00869**	-0.146
		(0.00485)	(0.00435)	(0.103)
Insured Flood Zone 100Y		0.00344***	0.00540***	0.00502***
		(0.00103)	(0.00114)	(0.00111)
Insured Flood Zone 100Y, Direct Impact		-0.00382**	-0.00376**	-0.00350***
		(0.00162)	(0.00162)	(0.00123)
Insured Flood Zone 500Y		0.000111	0.000974	0.00117*
		(0.000616)	(0.000637)	(0.000619)
Community Rating System Discount		0.0401**	0.0490**	0.0348**
		(0.0195)	(0.0200)	(0.0160)
Community Rating System Discount, squared		-0.222**	-0.221**	-0.167**
		(0.0909)	(0.0883)	(0.0774)
Within 200 yards from water		0.0197*	0.00137	-0.00387
		(0.0115)	(0.0120)	(0.0119)
Within 200 yards from water, squared		-0.0297*	-0.0109	-0.000447
		(0.0159)	(0.0160)	(0.0163)
Recreational-Use Housing			-0.00303	-0.00437*
			(0.00208)	(0.00235)
Income in 1999 below poverty level			0.000361	-0.00195
			(0.00450)	(0.00445)
House value 750K to 1M			-0.00206	-0.0472*
			(0.0326)	(0.0254)
House value over 1M			-0.0158	-0.000255
			(0.0106)	(0.0105)
Construction with 20 to 49 Units			-0.0625***	-0.0465**
			(0.0216)	(0.0229)
Construction with 50+ Units			0.0249*	0.0225
			(0.0139)	(0.0138)
Vacant			0.00626	0.0105**
			(0.00548)	(0.00523)
Rural			0.00557***	0.00552***
			(0.00176)	(0.00156)
Population 65 to 74 years old			0.0151	0.0118
			(0.0114)	(0.0105)
Observations	3,616	3,596	3,596	3,596
R-squared	0.095	0.145	0.154	0.171
State FE	Yes	Yes	Yes	Yes

Table A4: Expected Loss: Association with Observed Loss and County Characteristics

The table lists OLS estimates that describe the relationship between weather-related losses and predictions form the Random Forest algorithm, and between those predictions and county vulnerability and hazard frequency. Column (1) regresses losses on RF predictions. Column (2) regresses losses on a set of indicators for the state-specific county-risk decile. Higher decline is associated with higher expected loss within a given period. Columns (3)-(5) follow columns (1)-(3) in Table A3. Column (3)-(5) only show a subset of coefficients and omit the rest. Residuals are clustered by county. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Damage	Damage	Exp Damage	Exp Damage	Exp Damage
Exp Damage	0.720***				
	(0.0855)				
Risk Percentile = 2, 20th Risk Percentile		0.000594**			
		(0.000269)			
Risk Percentile = 3, 40th Risk Percentile		0.00163***			
		(0.000266)			
Risk Percentile = 4, 60th Risk Percentile		0.00382***			
		(0.000322)			
Risk Percentile = 5, 80th Risk Percentile		0.0137***			
		(0.00101)			
Hurricanes$_{t-1}$			0.00186***	0.00136***	0.00133***
			(0.000225)	(0.000158)	(0.000156)
Floods$_{t-1}$			0.000327	-0.000194	-0.000196
			(0.000226)	(0.000241)	(0.000232)
Storms$_{t-1}$			0.000234	0.000304**	0.000257*
			(0.000153)	(0.000141)	(0.000133)
Flood Zone 100Y				0.0359***	0.0363***
				(0.00624)	(0.00641)
Flood Zone 100Y, Direct Impact				0.0547**	0.0414
				(0.0249)	(0.0255)
Flood Zone 500Y				0.00897*	0.0106**
				(0.00497)	(0.00459)
Insured Flood Zone 100Y				0.00251***	0.00374***
				(0.000673)	(0.000725)
Insured Flood Zone 100Y, Direct Impact				-0.00187*	-0.00167
				(0.00100)	(0.00102)
Insured Flood Zone 500Y				-0.000492	-0.000117
				(0.000391)	(0.000402)
Community Rating System Discount				0.0314**	0.0343***
				(0.0133)	(0.0132)
Community Rating System Discount, squared				-0.170**	-0.164***
				(0.0663)	(0.0615)
Within 200 yards from water				0.0132*	0.00404
				(0.00677)	(0.00705)
Within 200 yards from water, squared				-0.0150	-0.00454
				(0.00939)	(0.00951)
Recreational-Use Housing					-0.00322***
					(0.00124)
Income in 1999 below poverty level					0.00144
					(0.00312)
House value 750K to 1M					-0.0103
					(0.0240)
House value over 1M					-0.0127*
					(0.00763)
Construction with 20 to 49 Units					-0.0566***
					(0.0159)
Construction with 50+ Units					0.0245**
					(0.0109)
Vacant					0.00743*
					(0.00379)
Rural					0.00323***
					(0.00105)
Population 65 to 74 years old					0.00534
					(0.00727)
Observations	3,616	3,616	3,616	3,596	3,596
R-squared	0.151	0.159	0.393	0.524	0.540
State FE	Yes	Yes	Yes	Yes	Yes

Table A5: Florida Counties: Clusters Matched by Risk, Population, Income per capita

The table lists averages for the 20 county clusters based on the k-means clustering algorithm. Counties are clustered by per-capita income, population, and Random-Forest-predicted losses. Expected Loss is the RF-predicted loss. Income and population are reported in multiple of 1,000. Observations refers to the number of county x five-year-period observations.

Cluster	Expected Loss	Per Capita Income	Population	Average Loss	Observations
1	0.020	20.655	1.005	0.021	8
2	0.006	35.329	104.378	0.004	12
3	0.024	25.002	3.357	0.028	16
4	0.021	39.008	175.384	0.008	4
5	0.017	26.150	9.111	0.022	20
6	0.014	35.499	10.585	0.015	12
7	0.014	35.935	245.305	0.010	4
8	0.011	25.254	8.058	0.009	24
9	0.013	53.436	15.009	0.017	12
10	0.012	56.185	129.051	0.007	4
11	0.008	29.758	17.847	0.005	20
12	0.014	18.909	1.281	0.008	12
13	0.008	24.309	3.113	0.007	24
14	0.011	40.187	92.876	0.001	4
15	0.018	37.924	57.986	0.010	4
16	0.009	31.397	50.460	0.012	16
17	0.010	44.468	21.934	0.002	8
18	0.007	35.196	28.143	0.003	20
19	0.016	61.819	31.002	0.008	4
20	0.039	28.150	1.082	0.070	4

Table A6: Florida Counties: Cluster #18 Matched by Risk, Population, Income per capita

The table lists all counties included in cluster 18 from Table A5. For additional information on variable definitions, please refer to Table A5.

County	Expected Loss	Per Capital Income	Population	Average Loss	Observations
12001	0.006	33.166	23.976	0.002	4
12019	0.007	33.459	17.622	0.005	4
12073	0.007	34.497	26.513	0.002	4
12081	0.008	37.580	31.462	0.002	4
12117	0.006	37.277	41.140	0.005	4

Figure A1: Historical Disasters and Current Damage

The figure plots coefficient estimates of the effect of lags of the number of disaster declarations for floods, hurricanes, and severe storms on current county damage. The estimation specification is described in Table A3 and corresponds to specification (1).