Seawalls and Stilts: A Quantitative Macro Study of Climate Adaptation

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December 11, 2018

Abstract

Investment in adaptation capital reduces the damage from extreme weather, mitigating the welfare cost of climate change. Federal aid for disaster relief reduces the net costs to localities that experience extreme weather, decreasing their incentives to invest in adaptation capital. We develop a heterogenous-agent macro model to quantify the relationship between adaptation capital, federal disaster policy, and climate change. We find that federal aid for disaster relief substantially reduces adaptation investment. However, the federal subsidy for adaptation more than offsets this moral hazard effect. We introduce climate change into the model as a permanent, increase in the severity of extreme weather. We find that adaptation reduces the welfare cost of this climate change by 15-20 percent.

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1 Introduction

Extreme weather events frequently occur throughout the US and can cause substantial damage. For example, 30 hurricanes have struck the US since 2000 and more than half of these storms have caused over one billion dollars in damage.[1] Federal aid can reduce the net costs to localities that experience extreme weather. Additionally, households and local governments can directly mitigate these costs by investing in capital whose primary purpose is to reduce extreme weather damage. Examples of such adaptation capital include sea walls, storm drains, and wind-proof garage doors.[2] While adaptation investments are possible in theory and certainly occur in practice, we have little evidence on the aggregate effects of adaptation on extreme weather damage, or on how incentives for adaptation investment are influenced by federal policy. Understanding these issues is particularly important, given the large predicted increases in extreme weather severity as a result of climate change (IPCC 2000; IPCC 2014).

This paper develops a quantitative macro model of adaptation investment. We focus explicitly on storm-related extreme weather such as tropical cyclones, blizzards, tornadoes, and heavy rain and snow storms.[3] The framework modifies the Aiyagari-style heterogeneous agent model (Aiyagari, 1994) to apply in a new setting with a continuum of heterogeneous localities that experience idiosyncratic extreme weather shocks. A "bad" extreme weather shock (e.g., a storm) destroys a fraction of the locality's capital stock. A social planner in each locality can invest in adaptation capital to reduce the damage from extreme weather, and can purchase insurance to partially smooth consumption.[4] A federal government taxes localities and uses the revenue for disaster aid and subsidies for adaptation investment, analogous to the functions of the Federal Emergency Management Agency (FEMA) in the

[1] Source: http://www.aoml.noaa.gov/hrd/tcfaq/E23.html and NCEI Billion dollar damage data.

[2] The Fourth National Climate Assessment Report emphasizes the importance of adaptation in response to climate change (USGCRP, 2018).

[3] Our analysis does not apply to non-storm related extreme weather such as wildfires or incidents of extreme heat.

[4] The calibrated price of insurance is greater than the actuarially fair value. In equilibrium, the planner chooses not to fully insure consumption.

US.

To obtain meaningful quantitative insights, the model must capture the effectiveness of adaptation capital at reducing the damage from an extreme weather event. We cannot estimate this relationship directly because we do not have comprehensive data on adaptation capital. Such data would require cost estimates of all large scale public adaptation investments, such as sea walls and city drainage systems, and of all small-scale private investments, such as the investment required to flood-proof a home or a business.[5] Instead, we discipline the model parameters using a method-of-moments approach that exploits variation in the frequency with which US counties experience extreme weather events, the severity of the events, and the FEMA aid that they receive from an event.

The extreme weather events modeled in the present paper are more frequent and less severe than "rare disasters" (Barro, 2006) or "catastrophes" (Pindyck and Wang, 2013). In particular, the calibration implies that in the average locality, extreme weather occurs approximately once every four years and destroys less than one percent of the capital stock. Thus, these events are part of the locality's regular weather patterns, as opposed to very rare and destructive incidents (like the Great Depression or a mega-virus), drawn from the far-right tail of a distribution.

We use our calibrated model to conduct two counterfactual experiments. In the first experiment, we analyze the effects of federal disaster policy on adaptation. The federal government has two main policy levers: (1) FEMA aid for disaster relief and (2) subsidies for adaptation investment. The provision of FEMA aid alone, reduces localities' incentives to invest in adaptation capital, increasing the realized damage from extreme weather.[6] However, the adaptation subsidies (provided through both FEMA and the US Army Corps of Engineers (USACE)) are designed to mitigate this moral hazard by reducing the relative price of

[5]The Fourth National Climate Assessment Report stresses that "it remains difficult...to tally the extent of adaptation implementation in the United States because there are no common reporting systems and many actions that reduce climate risk are not labeled as climate adaptation" (USGCRP (2018), Chapter 28).

[6]Lewis and Nickerson (1989) show theoretically that federal aid for disaster relief reduces individuals' expenditures to protect their property from harm.

adaptation investment.

To quantify these channels, we compute a series of counterfactual stationary equilibria in which we remove individual elements of federal disaster policy. Our results reveal large moral hazard effects from FEMA aid. Specifically, the provision of FEMA aid without a counteracting subsidy for adaptation reduces adaptation capital to zero.[7] This reduction in adaptation capital increases the damage from extreme weather by 2 billion in 2016 dollars each year. To put this result in perspective, storm-related FEMA aid averages 6.7 billion per year.[8] Thus, the increase in damage from moral hazard is over one quarter of the total FEMA aid each year. However, we find that this moral hazard is more than offset by the federal subsidy to adaptation. The total effect of federal disaster policy is to increase adaptation capital relative to the counterfactual equilibrium with no federal policy.

We conduct a second counterfactual experiment to evaluate the potential for adaptation to mitigate the welfare cost of climate change. We focus on one specific aspect of climate change predicted by the scientific literature, the increase in the severity of extreme weather (Villarini and Vecchi 2013; Villarini and Vecchi 2012). We calculate two climate change stationary equilibria, one in which adaptation can respond to the increase in weather severity and one in which it cannot. We find that adaptation increases considerably in response to climate change, reducing the associated welfare cost by 15-20 percent.

A caveat of the present paper is that we model only one type of adaptation, capital investment to reduce extreme weather damage. In practice, agents could also adapt to extreme weather by moving away from storm-prone areas. For example, agents could leave the low-lying coastal areas surrounding New Orleans or the tornado alley of the lower Midwest. However, ties to culture and family make many households reluctant to move,[9] and most

[7]Consistent with these results, Cohen and Werker (2008) find that expectations of international aid following a disaster reduce countries' investments in disaster preparedness.

[8]The average is taken over the period for which FEMA data are available, 2004-2016.

[9]Wallace and Schwartz, "Left to Louisiana's Tides, a Village Fights For Time", *New York Times*, February 24, 2018, https://www.nytimes.com/interactive/2018/02/24/us/jean-lafitte-floodwaters.html (accessed November 27, 2018).

communities are currently focused on adaptation investment instead of on migration.[10] To simplify the model, we focus only on adaptation capital; we do not allow migration. Our results should be viewed as the effects of federal policy and climate change on adaptation, holding the distribution of the US population constant.

This paper builds on an earlier environmental literature that analyzes the role of adaptation as a component of optimal or second-best climate policy.[11] These earlier papers typically model adaptation as a function that translates economic resources into a decrease in climate damage at each level of the atmospheric carbon concentration. Through a reduced-form channel, adaptation decreases all types of climate damage ranging from extreme weather to species loss to disease. Such a general model of adaptation makes it difficult to obtain a realistic calibration of the adaptation-related parameters. A primary contribution of the present paper is to model one particular type of adaptation, capital to reduce storm damage, in a way that is consistent with the historical data on extreme weather events and FEMA aid for disaster relief. This approach allows for an empirically-grounded calibration of the key model parameters.

The intuition for the calibration strategy derives from an empirical literature that treats adaptation as a latent variable. Since there are typically no direct measures of adaptation, this literature looks for evidence of adaptation from the frequency with which an area experiences an event, such as a hurricane or a very hot day, and a measure of the associated damage per event, such as mortality or crop loss.[12] Many of these papers find a negative relationship between frequency and damage, generating the important empirical insight that

[10] The Fourth National Climate Assessment Report states that "communities are currently focused more on capacity building and on making buildings and other assets less sensitive to climate impacts. Communities have been less focused on reducing exposure through actions such as land-use change (preventing building in high-risk locations) and retreat." (USGCRP (2018), Chapter 28).

[11] See for example Agrawala et al. (2011), Barrage (2015), Bosello et al. (2010), Brechet et al. (2013), DeBruin et al. (2009), Felgenhauer and Bruin (2009), Felgenhauer and Webster (2014), Kane and Shogren (2000), and Tol (2007). Bosello et al. (2011) provides a nice overview.

[12] A negative relationship between frequency and damage per event suggests that adaptation has occurred. Barreca et al. (2016), Gourio and Fries (2018), Heutal et al. (2017), Hsiang and Narita (2012), Keefer et al. (2011), and Sadowski and Sutter (2008) find evidence of a negative relationship, and thus suggest there is potential for adaptation. Dell et al. (2012) and Schlenker and Roberts (2009) do not evidence of this negative relationship. Hsiang (2016) provides a nice overview of this literature.

adaptation has occurred. We calibrate our structural model so that it is consistent with this earlier evidence and then use the model to run counterfactual experiments on the effects of federal policy and climate change on adaptation.

Finally, this paper contributes to the growing literature which uses macroeconomic models to study environmental policy.[13] Perhaps the two most closely related papers are Krusell and Smith (2017) and Bakkensen and Barrage (2018). Krusell and Smith (2017) develop a quantitative macro model with regional effects of climate change.[14] Bakkensen and Barrage (2018) incorporate extreme weather shocks into a macroeconomic model.[15] Neither of these papers directly model adaptation. In line with this earlier literature, the present paper modifies a quantitative macroeconomic model to study environmental policy. However, to our knowledge, this is the first paper to apply an Aiygari-style heterogenous agent model to a setting with extreme weather shocks and adaptation.

The paper proceeds as follows: Section 2 describes the model and Section 3 discusses the calibration. Section 4 reports the quantitative results. Finally, Section 5 concludes.

2 Model

Time is discrete and infinite. The economy is composed of N regions which are differentiated by their risk of an extreme weather event and the corresponding severity of the event. We use the term extreme weather event to refer to any severe storm-related weather including tropical cyclones, blizzards, tornadoes, or very heavy rain or snow. Each region i contains a continuum of measure one of ex-ante identical localities. Each locality, j, is populated by a unit mass of infinitely lived, identical agents. Agents can invest in adaptation capital to directly reduce the damage from extreme weather events. Additionally, agents

[13]Hassler et al. (2016), Heutal and Fischer (2013), and Hassler and Krusell (fourthcoming) provide nice overviews of this literature.

[14]However, unlike the present paper, they model a global economy in which increases in temperature operate through a region-specific damage function to reduce TFP.

[15]Specifically, they augment an AK-style endogenous growth model with cyclone shocks that destroy physical and human capital.

can purchase insurance and use precautionary savings to smooth consumption in the face of extreme weather shocks. A federal government taxes the localities and uses the revenue to provide aid for those localities that experience extreme weather and subsidies for investment in adaptation capital, analogous to actions of FEMA in the US.[16]

Each locality is run by a social planner who makes investment, consumption, and insurance decisions to maximize the expected lifetime welfare of households in her locality, taking the actions of other localities as given. In practice, adaptation capital can be either public or private. For example, an individual household can raise its house on stilts to reduce flood damage while a local government can construct a seawall to protect coastal properties from storm surges. Private investment in adaptation capital and the private purchase of insurance do not generate any local externalities in the model. For example, the flood damage for one household does not depend on whether the neighboring household raises its house on stilts or purchases flood insurance.

Since there are no local externalities from private adaptation in the model, the solution to this local planning problem is equivalent to a partially decentralized solution in which a planner makes public adaptation investment decisions only, taking into account households' private adaptation investments and insurance purchases. Given this equivalence, we present the model as a local social planning problem, its simplest possible form. We do not distinguish between public and private investments in adaptation capital, as this is not important for our quantitative conclusions.

2.1 Extreme weather and production

At the start of each period, t, locality j in region i experiences an extreme weather shock $\varepsilon_{ijt} \in \{0, 1\}$. We interpret $\varepsilon = 1$ as extreme weather occurs and $\varepsilon = 0$ as extreme weather does not occur. The extreme weather shocks are i.i.d across localities.[17] Variable p_i is the

[16]The population of each locality is fixed and normalized to unity; agents cannot migrate between localities.

[17]In practice, extreme weather shocks are spatially correlated. However, event severity held constant, the damage a locality experiences from an extreme weather event is independent of whether or not the neighboring

region-specific probability of an extreme weather event (e.g., the probability that $\varepsilon_{ijt} = 1$). By the law of large numbers, p_i corresponds to the fraction of localities in region i with $\varepsilon = 1$ in any period t.[18]

The realization of extreme weather destroys the productive capital stock, k^p. For example, consider a cyclone or tornado destroying the buildings, factories, and infrastructure in its path. Let k^d_{ijt} denote the capital stock destroyed by extreme weather in county j in region i in period t,

$$k^d_{ijt} = \varepsilon_{ijt}\Omega_i h(k^a_{ijt})k^p_{ijt}. \tag{1}$$

Parameter Ω_i determines the severity of the extreme weather event in region i; all else constant, increases in Ω_i imply that extreme weather destroys a larger fraction of the capital stock. Variable, k^a denotes the capital stock used for adaptation. The planner in each locality can invest in adaptation capital, k^a, to reduce the damage from extreme weather in her locality. Function $h(k^a)$ governs the process through which adaptation capital reduces damage. Function $h(k^a)$ is decreasing and convex in k^a, $h'(k^a) < 0$, $h''(k^a) > 0$, implying that there are diminishing returns to adaptation capital. For example, a planner might first install storm drains and then build a levee. Compared to the levee, the storm drains are relatively cheap and more effective per dollar spent.

After the realization of the extreme weather shock, firms in each region, i, in each locality, j, produce a homogeneous final good, y_{ij}, from labor, l_{ij}, and the non-destroyed productive capital, $\tilde{k}^p_{ij} \equiv k^p_{ij} - k^d_{ij}$, according to the Cobb-Douglas production function $y_{ij} = (\tilde{k}^p_{ij})^\alpha l_{ij}^{1-\alpha}$. The final good is the numeraire.

locality also experiences an extreme weather event. Given this independence, the spatial correlation of extreme weather shocks is not important for the paper's quantitative results.

[18]Recent empirical studies suggest that agents do not internalize the true probability of extreme weather into their decision making process (Bin and Landry (2013) and Kousky (2010) and Gallagher (2014)). In particular, Gallagher (2014) shows that a Bayesian model in which agents update their flood risk beliefs based on recent flood experiences and then "forget" flood experiences farther in the past can match these empirical patterns. Modeling the planner's beliefs using Gallagher (2014)'s partial information model of Bayesian updating does not substantially change the aggregate implications of the model.

The total damage from an extreme weather event includes two costs: (1) the destroyed capital and (2) the forgone period t output as a result of the destroyed capital. Localities incur the second cost because the extreme weather shock realizes at the start of period t, before the production takes place. The total damage for locality j in region i in period t is,

$$d_{ij} = [(k_{ij}^p)^\alpha l_{ij}^{1-\alpha} + (1-\delta)k_{ij}^p] - [(\tilde{k}_{ij}^p)^\alpha l_{ij}^{1-\alpha} + (1-\delta)\tilde{k}_{ij}^p].$$

The first term is the end-of-period value of production and non-depreciated capital if there were no extreme weather shocks. The second term is the corresponding value when there are extreme weather shocks. If $\varepsilon = 0$, then $\tilde{k}^p = k^p$, implying that $d = 0$.

2.2 Private insurance

The insurance market is designed to capture the consumption-smoothing opportunities provided by homeowners insurance and the National Flood Insurance Program (NFIP). We assume that perfectly competitive firms provide insurance at constant marginal cost, λ.

At the end of each period t, the local planner chooses her level of insurance coverage for the next period, x_{ijt+1}. If extreme weather occurs in period $t+1$, the planner receives the value of her insurance. If no extreme weather occurs, the planner receives zero.[19] The insurance premium per dollar of insurance, q_i, equals the expected payout, p_i, plus the marginal cost, λ,

$$q_i x_{ij,t+1} = (p_i + \lambda) x_{ijt+1}.$$

The planner pays the premium for period $t+1$ insurance in period $t+1$.[20] Summing across

[19]We focus on the empirically relevant region of the parameter space where the value of the insurance is less than the value of damage. We could extend the notation to allow for the case where the value of insurance exceeds the damage. In that circumstance, the agent would receive the minimum of the insurance coverage and the value of the damage.

[20]This timing assumption avoids introducing an interest rate into the planner's valuation of the insurance. An equivalent alternative assumption would be that the planner chooses insurance at the start of the period, before the shock realizes.

localities in any period t, the law of large numbers implies that the insurance premiums equal insurance claims plus the cost of providing the insurance.

The planner can also self-insure against extreme weather through precautionary savings in productive and adaptation capital. That is, she can accumulate "extra" capital which she can convert into consumption when a bad extreme weather shock realizes. The planner's allocation between private insurance and precautionary savings depends on the relative price of each consumption-smoothing instrument.

2.3 Federal government

The purpose of the federal government in our model is to capture the benefits and incentives for adaptation created by federal disaster policy in the US. FEMA provides aid for counties that experience extreme weather. FEMA and the US Army Corps of Engineers (USACE) provide subsidies for adaptation investment. Our model federal government preforms both of these functions. Aid for extreme weather equals ψd_{ijt}, where $\psi \epsilon [0, 1]$ is the fraction of damage covered by the aid.

The adaptation subsidy, s, reduces the relative price of adaptation investment. Specifically, the law of motion for adaptation capital in locality j in region i is,

$$k^a_{ij,t+1} = (1 - \delta)k^a_{ijt} + (1 + s)i^a_{ijt}.$$

One additional unit of adaptation capital only costs the locality $1/(1 + s)$ units of final good. Grants for adaptation capital from both FEMA and the USACE impose a cost-sharing requirement on the locality, effectively reducing the relative price of adaptation capital funded through the grant. For example, FEMA hazard mitigation grants require that 25 percent of the project be financed with non-federal dollars.[21] Similarly, USACE financed flood-control and hurricane damage projects require the locality to finance 35-50

[21] See www.fema.gov/hazard-mitigation-grant-program

percent of the overall cost.[22]

Our model government finances the FEMA aid and adaptation subsidies with uniform lump sum taxes, T_t, on the household. In practice, FEMA and the USACE are financed through federal income taxes. Localities do not pay differential taxes based on the likelihood that they will receive FEMA aid or adaptation subsidies. Uniform lump-sum taxes on households incorporate this feature of the data.

2.4 Optimization

The planner in each locality divides output among consumption, investment in productive and adaptation capital, and insurance premiums. Productive and adaptation capital accumulate according to the standard law of motion,

$$k^p_{ij,t+1} = (1-\delta)\tilde{k}^p_{ijt} + i^p_{ijt} \quad \text{and} \quad k^a_{ij,t+1} = (1-\delta)k^a_{ijt} + (1+s)i^a_{ijt},$$

where δ is the depreciation rate of capital and s is the adaptation subsidy. Variables i^p and i^a denote investment in productive and adaptive capital, respectively.

Following the realization of the extreme weather shock, the planner chooses consumption, both types of investment, and next period's level of insurance coverage to maximize the expected lifetime welfare of the representative household. The planner's value function is given by,

$$V(k^a_{ij}, k^p_{ij}, x_{ij}; \varepsilon_{ij}) = \max_{(k^a_{ij})', (k^p_{ij})', (x_{ij})'} \left\{ u(c_{ij}) + \rho EV((k^a_{ij})', (k^p_{ij})', x'_{ij}; \varepsilon'_{ij}) \right\} \tag{2}$$

subject to the damage from extreme weather (equation (1)), and the locality's resource constraint,

$$c_{ij} = y_{ij} + \varepsilon_{ij} x_{ij} + \psi d_{ij} - i^a_{ij} - i^p_{ij} - T - q_i x_{ij}. \tag{3}$$

[22]See http://www.mvr.usace.army.mil/Portals/48/docs/RE/Guide/WhoPays.pdf

Prime superscripts denote the next period's value of the variable. Function $u(c)$ denotes household utility and c denotes consumption. The planner forms her expectation over ε'_{ij} based on the regional probability of extreme weather, p_i.

An underlying assumption embedded in the resource constraint (equation (3)) is that the representative agent's wealth is entirely contained within her locality. In practice, of course, this is not true. Households can own stock which exists outside the locality and thus would not be destroyed by an extreme weather event. However, for most households, the share of stock holdings relative to total assets is small, making the assumption that all wealth is local more reasonable. For example, Wolff (2017) calculates that stocks account for less than 10 percent of middle class assets.[23] Furthermore, many of these stock holdings are tied up in retirement accounts; less than 5 percent of middle class assets are direct holdings of corporate stock, financial securities, mutual funds, and personal trusts. Thus, for the typical US citizen, the vast majority of wealth is locally owned.[24]

2.5 Stationary equilibrium

We define a stationary equilibrium in which aggregate macroeconomic variables are constant. We suppress the t subscripts throughout the stationary equilibrium definition; we signify a planner's chosen levels of capital and insurance coverage in the next period as k' and x'. The local state variables are adaptation capital, k^a_{ij}, productive capital, k^p_{ij}, the level of insurance, x_{ij}, and the current realization of extreme weather ε_{ij}. Let z denote the vector of these state variables. The summations are taken over the distribution of localities over the state space, z.

[23]The term middle class household refers to a household with wealth in the middle three wealth quintiles.

[24]Relaxing the assumption that all wealth is local considerably complicates the model and introduces assumptions that make the underlying mechanisms governing adaptation investment less transparent. For example, one could incorporate a portfolio choice where households allocate their wealth between local and non-local capital. This introduces an additional state variable. Furthermore, under this setup, households would choose to fully diversify, investing all of their wealth in non-local capital. Matching the empirical fact that most household wealth is local would require an additional behavioral assumption or underlying preference for local capital. Given, that almost all wealth for the typical US household is local, we choose to abstract from modeling the portfolio choice between local and non-local capital and thus avoid the associated complications.

Given the level of FEMA aid, ψ, the adaptation subsidy, s, the probability of an extreme weather event, p_i, a stationary equilibrium consists of planners' decision rules $\{c_{ij}, k_{ij}^{a'}, k_{ij}^{p'}, x'_{ij}\}$, lump sum taxes, T, and the joint distribution of localities $\Phi(z)$, such that the following holds:

1. The social planner in each region solves the optimization problem in Section 2.4.

2. The government budget balances:

$$\sum T\Phi(z) = \sum[\psi d_{ij} + s i_{ij}^{a}]\Phi(z)$$

3. The aggregate resource constraint holds:

$$Y + (1-\delta)(K^a + \tilde{K}^p) = C + K^{a'} + K^{p'}$$

   where

$$\tilde{K}^p = \sum \tilde{k}_{ij}^{p}\Phi(z), \quad K^a = \sum k_{ij}^{a}\Phi(z), \quad Y = \sum y_{ij}\Phi(z), \quad \text{and} \quad C = \sum c_{ij}\Phi(z)$$

4. The distribution, $\Phi(z)$, is stationary.

To summarize, the planner has three channels through which she can mitigate the welfare consequences of extreme weather events. First, she can invest in adaptation capital to directly reduce the damage caused by extreme weather. Second, she can purchase insurance to smooth consumption between the states of the world when a bad extreme weather shock realizes and those when it does not. And three, she can further smooth consumption through precautionary savings.

2.6 Discussion: incentives for adaptation investment

To help build intuition for how climate change and federal disaster policy affect adaptation incentives, we analyze the planner's first order condition for adaptation capital. The first order condition for adaptation capital in locality j in region i is

$$u'(c_{ij}) = \beta(1-p_i)u'(c'_{ij}|\varepsilon'_{ij}=0)[R^a_{ij}(0)+1-\delta] + \beta p_i u'(c'_{ij}|\varepsilon'_{ij}=1)[R^a_{ij}(1)+1-\delta], \quad (4)$$

where

$$R^a_{ij}(\varepsilon_{ij}) = \begin{cases} 0 & : \varepsilon_{ij}=0 \\ (1-\psi)(1+s)(-h'(k^a_{ij}))\left[\alpha(k^p_{ij})^\alpha(1-\Omega_i h(k^a_{ij}))^{\alpha-1} + (1-\delta)k^p_{ij}\Omega_i\right] & : \varepsilon_{ij}=1 \end{cases}$$

Variables $R^a(0)$ and $R^a(1)$ denote the realized return to adaptation capital when $\varepsilon'=0$ and $\varepsilon'=1$, respectively. If there is no extreme weather, $\varepsilon'=0$, then the return to adaptation capital is zero. This result is intuitive. For example there is no benefit to elevating a structure on stilts if there is not a storm.

When extreme weather occurs, $\varepsilon'=1$, the return to adaptation is positive and is composed of two parts that parallel the damage from extreme weather. First, adaptation reduces the output loss in the period the extreme weather occurs, captured by the term $\alpha(k^p_{ij})^\alpha(1-\Omega_i h(k^a_{ij}))^{\alpha-1}$. Second, adaptation reduces in the loss in the non-depreciated productive capital, captured by the term $(1-\delta)k^p_{ij}\Omega_i$. Incentives for adaptation are increasing in the probability of an extreme weather event, p_i, since the return is positive when $\varepsilon'=1$ and zero otherwise. Thus, adaptation capital should be larger in areas that more frequently experience extreme weather.

We discuss the effects of changes in federal disaster policy, captured by parameters s and ψ, and changes in event severity brought about by climate change, captured by parameter Ω. We focus on the partial-equilibrium effects of changes in these variables, holding consumption and productive capital constant.

Federal disaster policy creates opposing incentives for adaptation. The return to adaptation is decreasing in the level of FEMA aid, ψ, and increasing in the subsidy, s. The locality's incentives for adaptation depend only on the fraction of damage, $1-\psi$, that it experiences, not on the total damage. Higher levels of FEMA aid reduce the damage the locality experiences, reducing the return to adaptation. The subsidy counter-acts these effects of FEMA aid by increasing incentives for adaptation. Each unit of expenditure on adaptation capital generates $1+s$ unites of investment, magnifying the associated return by $1+s$.

The return to adaptation capital is increasing in the extreme weather severity, Ω_i. This relationship implies that regions with more severe extreme weather have higher levels of adaptation capital. Moreover, increases in extreme weather severity from climate change increase incentives for adaptation investment.

3 Calibration and functional forms

The time period for the calibration is one year. We map localities in the model to counties in the US. To divide the counties into different risk regions, we need to define when a county experiences an extreme weather event. Following Gallagher (2014), we use Presidential Disaster Declarations (PDDs) as a source for extreme weather events. We say that a county experiences an extreme weather event in year t if it experiences at least one storm-related weather incident in year t that received a PDD.[25] An extreme weather event receives a PDD when the damage is sufficiently large such that it is beyond state and local capabilities to address.[26]

We divide the US counties into two risk regions, low and high, based on the annual probability of an extreme-weather event. For each county, we calculate the probability of an extreme-weather event as the number of extreme-weather events during the 29 years for

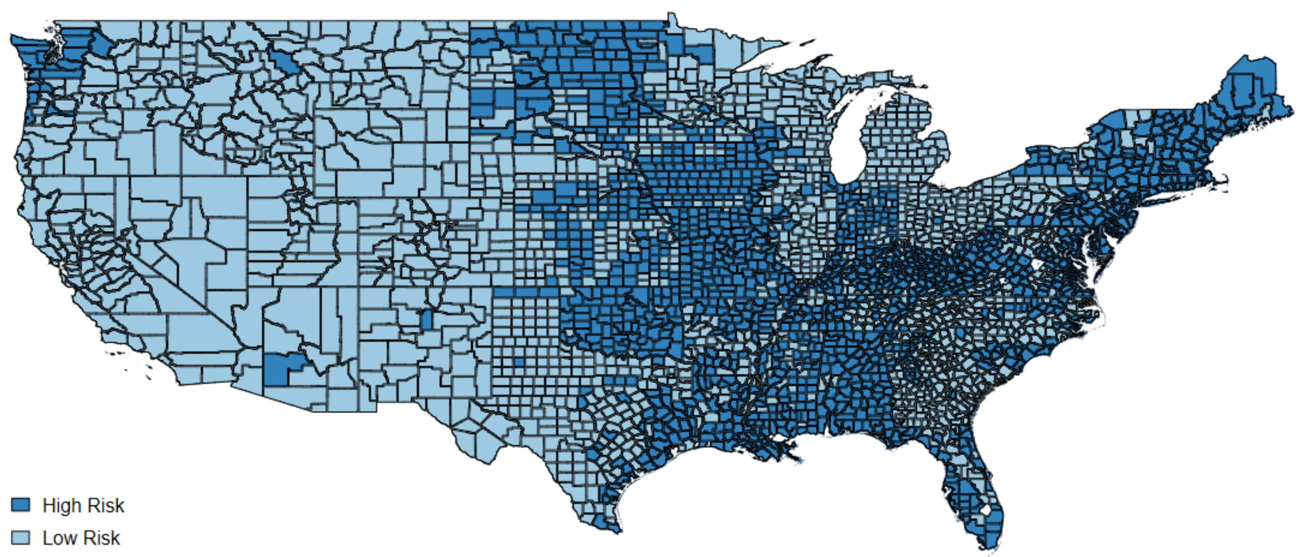
[25]The main storm-related weather incidents in our analysis are tropical cyclones, blizzards, tornadoes, and other heavy rain or snow storms.

[26]To request a PDD for extreme weather, local government officials partner with FEMA regional officials to conduct a preliminary damage assessment. The assessment includes estimates of the total damage from the event, the unmet needs of individuals, families, businesses, and the impact to public property. If the total damage is so large that it is beyond state and local capabilities to address, the state governor can request a PDD from the FEMA regional director who can, in turn, request a PDD from the US president (FEMA, 2003). Specifically, the total damage must exceed 1.30 per capita in 2011 dollars to warrant a PDD (McCarthy, 2011).

which consistent data on PDD events are available (1989-2016) divided by the total number of years.[27] We define a county as low risk if its probability of an extreme weather event is less than 30 percent and high risk if its probability of extreme weather is greater than 30 percent.[28] The average probability of an event in the low- and high-risk regions is 0.17, and 0.38, respectively.

Figure 1 shows a map of the different counties shaded according to their risk region. The high-risk counties are predominately located in coastal areas that are susceptible to hurricanes and tropical storms, and in the Midwest where severe storms are also common. Per-capita income in 2016 is similar across the high- and low-risk regions, equal to 40,809 in the low-risk region and 40,748 in the high-risk region (in 2016 dollars). Approximately 52 percent of the 2016 US population lives in high-risk counties, while 54 percent of 2016 aggregate income derives from these counties.[29]

Figure 1: Map of US Counties By Risk Level



While major extreme weather events, such as Hurricanes Katrina and Sandy, receive

[27]We begin in 1989 because the Stafford Act, passed in 1988, considerably changed the FEMA system (FEMA, 2003).

[28]We set the cutoff at 30 percent to divide the US population as equally as possible between the high- and low-risk counties.

[29]County-level data on personal income are from the Bureau of Economic Analysis, downloaded on 1/18/2018.

PDDs, many smaller, less newsworthy events also receive PDDs. On average, one quarter of all US counties receive a storm-related PDD each year. Thus, the typical PDD is simply part of the regular weather pattern in a region, and not an extremely rare, news-headline event.

One potential concern with using PDD events to indicate extreme weather is that politics could affect the declaration of a presidential disaster. For example, presidents may be more likely to issue a disaster declaration in states with large swing voter populations or in states with political ties to the White House or to congressional committees that oversee FEMA (Davlasheridze et al. 2014; Garrett and Sobel 2007; Reeves 2011).

However, for politics to affect our calibration, there would need to be systematic differences in the political power across the low- and high-risk counties over the 1989-2016 time period. For example, we might worry that the high-risk counties are high risk because they are more politically connected and thus able to declare more disasters. However, the location of the high- and low-risk counties in Figure 1 suggests that this is not the case. The high-risk counties are primarily in areas with a high meteorological risk of extreme weather (e.g. the gulf coast) and in states that span the political spectrum from Texas on the right to New York on the left. Additionally, there was a lot of political turmoil during the 1989-2016 time period with presidents and house and senate majority leaders from both parties, major within party divisions, and lots of turnover on the congressional FEMA oversight committees (Davlasheridze et al., 2014). Such turmoil makes it difficult for any particular county to consistently receive political favors in the form of PDDs over this period.

Our calibration strategy will also require a county-level measure of damage from extreme weather. Direct damage estimates are not available at the county-level.[30] Instead, we use

[30] The Spatial Hazards and Losses Database for the United States (SHELDUS) reports county-level damage information for extreme weather events in the US. However, if only region (e.g. multi-county) damage estimates are available, SHELDUS distributes the losses equally across all involved counties (cemhs.asu.edu/sheldus/metadata), implying that the county-level estimates are subject to large errors. Furthermore, even with these imputations, the data are severely incomplete. The primary source of the data are self-reports by individual weather stations and as a result, many observations are missing. In particular, Gallagher (2014) reports that only 8.6 percent of flood-related PDD events from 1960-2007 are included in SHELDUS and many of those events have no reported damage. As Gallagher (2014) notes, this

data on FEMA aid to measure damage.[31] To calculate FEMA aid for a year-t extreme-weather event, we take the sum of all FEMA aid from all events that occurred in year t in the specific county. For example, in 2005, Acadia Louisiana experienced two different PDD events (from hurricanes Katrina and Rita) and received approximately 31 million (in 2005 dollars) in FEMA aid for both events combined. We code this observation as Acadia experienced an extreme-weather event in 2005 with aid payments equal to 31 million. Complete data on FEMA aid is available from 2004-2016.[32]

An important assumption for our calibration strategy to be meaningful is that FEMA aid is proportional to damage, on average. In particular, we must check that the fraction of damage the county receives in FEMA aid, ψ, is uncorrelated with total damage from the event. For example, if this assumption did not hold, then one might worry that more severe events would receive a smaller fraction of damage in FEMA aid because of government budget constraints. If counties in the high-risk region systematically experience more severe extreme weather, then these budget constraints imply that the high-risk counties would also systematically receive a smaller fraction of damage in FEMA aid.

To rule out this possibility, we construct an event-level measure of FEMA aid relative to damage. While county-level damage estimates are not available, event-level damage and fatality estimates for almost all tropical cyclones are available from NOAA's tropical cyclone reports. Additionally, estimates of the direct damage and deaths for large disasters (those with more than one billion dollars in estimated damage) are available from the Billion-Dollar Weather and Climate Disasters database assembled by NOAA's National Center of Environmental Information.[33] Combined, NOAA's tropical cyclone reports and NCEI database

is implausible, since damage estimates are prerequisite to a PDD declaration.

[31] A PDD authorizes the federal government to provide disaster aid through FEMA. FEMA aid includes both direct assistance to households through the Individuals and Households program (IHP) and assistance to local governments through the Public Assistance program (PA). Examples of IHP aid include grants to help pay for emergency home repairs, temporary housing, personal property loss, and medical, dental and funeral expenses caused by the disaster. Examples of PA aid include funds for emergency relief and to repair or replace damaged public infrastructure. Data is available from fema.gov.

[32] Specifically, data on IHP aid is available from fema.gov from 2004-2016 and data on PA aid is available from fema.gov from 1998-2016.

[33] To account for uninsured or under-insured losses, NOAA scales up insured loss data by a factor equal to

cover over half of the PDD events in our sample. Using the NOAA data, we define the damage from an event as the direct damage and plus any reported deaths multiplied by the value of a statistical life.[34]

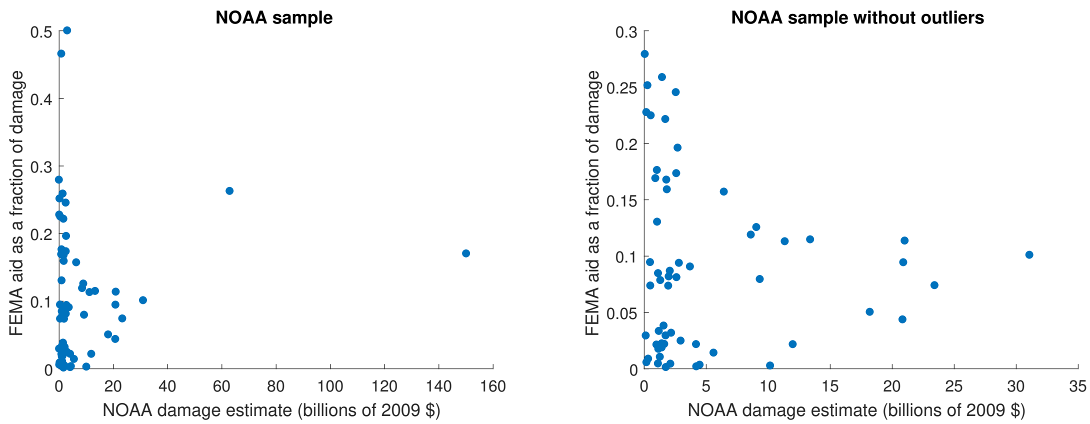
The left panel of Figure 2 plots FEMA aid as a fraction of damage for each event in the NOAA sample. Hurricanes Katrina and Sandy are two clear outliers with damage estimates of 63 and 150 billion in 2009 dollars, respectively. Similarly, midwest storms in 2008 and 2010 are also outliers with FEMA aid as a fraction of damage equal to 0.5 and 0.46, respectively. The right panel of Figure 2 plots the data without these outliers. Visually, there is not an obvious correlation between damage and the fraction of FEMA aid. Empirically, the correlation coefficient between these two variables is not statistically different from zero with a p-values of 0.41 in the full sample and 0.52 in the sample without outliers. Furthermore, regressing FEMA aid as a fraction of damage on the total damage yields a coefficient estimate of 5.73e-13 with a standard error of 6.86e-13.[35] Based on this evidence, we conclude that a systematic correlation between damage and FEMA aid as a fraction of damage is highly unlikely.

the reciprocal of the insurance participation rate in that region. For example, if a region had approximately 50 percent policy protection under the National Flood Insurance Program (NFIP), NOAA would apply a factor of two to the region's NFIP claims in their calculation of total losses. We interpret the NOAA damage estimate as the actual damage from any extreme-weather event that is included in the NOAA data.

[34]We use the EPA's value of 7.6 million (in $2006) for the value of a statistical life (see www.epa.gov/environmental-economics/mortality-risk-valuation).

[35]Similarly, in the sample without outliers, the coefficient estimate on total damage equals -1.01e-12 with a standard error of 1.56e-12.

Figure 2: FEMA Aid as a Fraction of Damage For Extreme Weather Events



3.1 Parameter values and functional forms

The calibration has two steps. In the first step, we choose parameter values for which there are direct estimates in the data. In the second step, we calibrate the remaining parameters so that certain targets in the model match the values observed in the US economy. Table 1 reports the parameter values.

Table 1: Calibration Parameters

Parameter	Value	Source
Production		
Depreciation: δ	0.094	Method of moments
Capital's share: α	0.33	Data
Productivity: A	1	Normalization
Preferences		
Discount factor: ρ	0.975	Method of moments
CRRA coefficient: σ	2	Assumption
Federal policy		
Adaptation subsidy: s	0.25	Method of moments
FEMA aid: ψ	0.106	Data
Insurance cost: λ	0.0019	Method of moments
Extreme weather and adaptation		
Low risk probability: p_l	0.175	Data
High risk probability: p_h	0.38	Data
Low risk event severity: Ω_l	0.0062	Method of moments
High risk event severity: Ω_h	0.0094	Method of moments
Adaptation: θ	7.88	Method of moments

3.2 Production

We set productive capital's income share, α, equal to one third. We normalize total factor productivity to unity. We determine the depreciation rate, δ, to match the US investment-output ratio of 0.255 (Conesa et al., 2009).

3.3 Preferences

We use CRRA utility, $u(c) = c^{1-\sigma}/(1-\sigma)$. We set the coefficient of relative risk aversion equal to the standard value of 2. We determine the discount rate, ρ, to match the US capital-output ratio of 2.7 (Conesa et al., 2009).

3.4 Extreme weather and adaptation

We use a simple functional form for $h(k^a)$ that is decreasing and convex in k^a,

$$h(k^a) = \frac{1}{1 + \theta k^a}. \tag{5}$$

Parameter θ determines the effectiveness of adaptation capital. We discuss the calibration of parameter θ together with the severity parameters, Ω_h and Ω_l.

The intuition for the calibration of θ borrows from the empirical literature that treats adaptation as a latent variable.[36] This literature estimates the relationship between the frequency with which an area experiences an extreme weather event and the associated damage per event. If areas that more frequently experience extreme weather have lower damage per event, then the literature interprets this negative relationship as evidence of adaptation. We will use this same type of variation to pin down the key parameter for adaptation in our structural model, θ.

For example, suppose that extreme weather events in the high-risk region are twice as severe as extreme weather events in the low-risk region (e.g., $\Omega_h/\Omega_l = 2$). Then, if it is not possible to adapt ($\theta = 0$), we would expect damage per event in the high-risk region to be twice as high as damage per event in the low-risk region. However, if it is possible to adapt, then damage per event in the high-risk region should be less than twice as high as damage per event in the low-risk region, because the high-risk region faces stronger incentives to invest in adaptation capital. How much less depends on the value of θ.

To implement this calibration strategy for θ, we need to calibrate the relative severity of an event in the high-risk region compared to in the low-risk region (Ω_h/Ω_l). Our measure of the relative severity of an event must be independent of the level of adaptation. Therefore, we cannot use data whose value is affected by adaptation. For example, suppose we naively set

[36] See, for example: Barreca et al. (2016), Gourio and Fries (2018), Heutal et al. (2017), Hsiang and Narita (2012), Keefer et al. (2011), Sadowski and Sutter (2008) Dell et al. (2012) and Schlenker and Roberts (2009). Hsiang (2016) provides a nice overview of this literature.

the relative severity parameter equal the ratio of FEMA aid in the high-risk region relative to FEMA aid in the low-risk region. If counties in the high-risk region have larger stocks of adaptation capital, then this aid ratio would be smaller than the true value of relative severity.

To address these concerns, we calibrate the relative severity from within county variation in the type of event and the associated FEMA aid, and from a meteorological measure of cyclone severity. We split extreme-weather events in each county into cyclone and non-cyclone events.[37] In our model, there is just one type of extreme weather (corresponding to $\varepsilon = 1$). Therefore, to map the model to the data, we must calculate the relative severity of the average event in each region. The severity of this average event is a weighted mean of the severities of cyclone and non-cyclone events.

We normalize the severity from a non-cyclone in the low-risk region to unity and compute the severity for the remaining three categories, given this normalization. The first two rows of Table 2 report the severity in each category. We discuss how to compute each box in turn.

Table 2: Severity by Event Type and Risk Region

	Low risk	High risk
Non-cyclone	1	1.02
Cyclone	7.75	12.24
Weighted average	**4.37**	**6.63**

To calculate the severity of a cyclone event in the low-risk region, we analyze the subsample of low-risk counties that experienced both cyclone and non-cyclone events. We compute the ratio of FEMA aid for cyclone events relative to non-cyclone events within each of these counties. Taking the average across all low-risk counties in the subsample, yields a value of

[37] Our analysis is at the annual level. We define a county to have a cyclone event in year t if it experienced one or more cyclones in year t, and zero non-cyclones. Similarly, we define a county to have a non-cyclone event in year t if it experienced one or more non-cyclones in year t and zero cyclones. In 2.5 percent of the county-year observations, counties experience both cyclones and non-cyclones in a given year. We duplicate the observations for these county-years and assign one duplicate the FEMA aid for all cyclones in that county-year and assign the other duplicate the FEMA aid for all non-cyclones in that county-year.

7.75. We interpret this average as a primitive parameter that applies to all low-risk counties, implying that the damage from the average cyclone event in a low-risk county is 7.75 (second row, first column of Table 2). This calculation assumes that the adaptation capital in a county has the same effect on damage from a cyclone as it does on the damage from a non-cyclone. For example, the effect of a drainage system on flood damage is independent of the type of storm that caused the rain. Similarly, the effect of a wind-proof garage door or a roof with hurricane straps on wind-damage is independent of the type of storm that caused the wind.

To calculate the severity of a cyclone in the high-risk region, we use data on cyclone wind speed. Wind speed is a common summary statistic for cyclone severity. For example, the cyclone's wind speed determines its category on Saffir-Simpson scale and the associated damage predictions. Several empirical studies estimate the relationship between a cyclone's wind speed and the resulting damage. Estimates based on global data typically find that cyclone damage increases with the cube of maximum sustained wind speed (Emanuel 2005). However, Bakkensen and Mendelsohn (2016) argue that the US is an outlier in this relationship; they find that US cyclone damage is proportional to the fifth power of maximum wind-speed. Similarly Nordhaus (2010) estimates that US cyclone damage is proportional to the eighth power of maximum sustained wind speed.[38] Based on his estimates, Nordhaus (2010) argues that it is "extremely unlikely that the [US wind-damage] elasticity is less than five." Following this earlier literature, we use the fifth power of the maximum sustained wind speed in each county that experiences a cyclone to measure the cyclone's severity in that county.

Data on the location, maximum sustained wind speed, and wind radii at six hour time steps are available from NOAA's best track dataset and extended best track dataset for

[38]The primary differences between the main specifications in the two papers are the treatment of GDP and population and the time period for the analysis. Specifically, Bakkensen and Mendelsohn (2016) include both population an GDP as control variables, and their estimation covers the period from 1960-2010. Nordhaus (2010) uses cyclone cost normalized by GDP as the dependent variable and does not include a separate population control. His main analysis covers the period from 1900-2008.

Atlantic and Pacific cyclones.[39] For each cyclone-county pair, we calculate the wind speed that the county experienced during each time step of the storm. Specifically, for every time step in the storm track, we check if the county intersects each of the four wind bands (maximum wind, 64 knots, 50 knots, and 34 knots). We take the maximum over all the time steps to calculate the maximum wind speed the county experienced from the cyclone.[40]

The ratio of the average of the fifth power of maximum sustained wind speed for high-risk-county cyclones relative to low-risk-county cyclones equals 1.58, implying that the average cyclone that strikes the high-risk region is 58 percent more severe than its low-risk counterpart. Thus, the severity from the average high-risk cyclone is $1.58 \times 7.75 = 12.24$ (second row, right column of Table 2).[41]

We compute the severity of a non-cyclone event in the high-risk region based on the severity of a cyclone event in the high-risk region and the within-county differences in FEMA aid for cyclones compared to non-cyclones in the high-risk region. Using the same process as in the low-risk region, we find that cyclone events are 11.94 times as severe as non-cyclone events in the high-risk region. This result implies that the severity of a non-cyclone event in the high-risk region is $12.24/11.94 = 1.02$ (first row, right column of Table 2).

Finally, to calculate the severity of the average event in each region (third row of Table

[39] The NOAA best track data can be downloaded from: www.nhc.noaa.gov/data/. This dataset contains all information except the wind radii for the maximum sustained wind speed. The NOAA extended best track data set can be downloaded from: rammb.cira.colostate.edu/research/tropical_cyclones/tc_extended_best_track_dataset/ This dataset includes the radii for the maximum sustained wind speed, as well as all the information in the NOAA best track data.

[40] Note that a small fraction of counties receive FEMA aid for a particular cyclone but do not fall within the cyclone wind-bands at any point on the cyclone's storm track. We first check to see if this is due to measurement error. NOAA wind radii estimates have a negative bias and the error can range from 25-40 percent (Knaff and Sampson (2015); Knaff and Harper (2010); Sampson and Knaff (2015)). To account for this error, we create an extended 34 knot wind-band that has radii equal to 140 percent of the original radii, incorporating the maximum error estimate of 40 percent. If the county falls within this extended 34-knot wind-band, we assign it a maximum sustained wind speed of 34 knots. If the county does not fall within this extended 34-knot wind band, we assign it a wind speed equal to one half of the minimum of 34 and maximum sustained wind speed at the point where the storm was closest to the county. The results are quantitatively similar if we assign these counties a maximum sustained wind speed anywhere between 0 and 34.

[41] Note that the same cyclone could strike the high- and low-risk counties. However, the results imply that, on average, the cyclone is stronger when it hits the high-risk counties then when it hits the low risk counties.

2), we average the severity values for the cyclone and non-cyclone events in each region and weight by the region-specific fractions of cyclone and non-cyclone events.[42] We find that the average event in the high-risk region is 1.52 times as severe as in the low-risk region, yielding the relative severity target $\Omega_h/\Omega_l = 1.52$

We compare the relative severity of an extreme weather event to the relative damage per event. To measure relative damage, we use the ratio of FEMA aid per event in the high risk region relative to the low risk region. The average value of this ratio is 1.36.[43] Thus, our results imply that while events that hit high risk counties are 52 percent more severe then those that hit low-risk counties, $\Omega_h/\Omega_l = 1.52$, the events only cause 36 percent more damage. The difference between the relative FEMA aid per event and the relative severity is indicative of the effectiveness of adaptation, and thus pins down θ.

Finally, to pin down the levels of FEMA aid and event severity, we choose Ω_l to target the ratio of FEMA aid per event relative to county income in low-risk counties. The average value of this ratio from 2004-2016 is 0.0019. To summarize, we use the following three targets to (primarily) pin down the three parameters, θ, Ω_h, and Ω_l: (1) relative severity, (2) relative FEMA aid, (3) average FEMA aid per event divided by county income in the low-risk region.[44]

A potential concern with the above calibration is that the average fraction of damage covered by FEMA aid, ψ, is not the same in the high- and low-risk regions. Fraction ψ could vary across regions if there are persistent political differences between the two regions or if ψ is correlated with damage (since high-risk events are more severe on average). However, as argued in Section 3, systematic differences in political power across the two regions are unlikely and there is no statistical correlation between FEMA aid as a fraction of damage and the total damage. We conclude that the regional differences in FEMA aid per event are

[42]The fraction of cyclone events are 0.17 and 0.15 in the high- and low-risk regions, respectively.

[43]We take this average over 2004-2016, the time period for which complete data on FEMA aid is available.

[44]All parameters are jointly determined by all of the moments, we cannot pin down some parameters from the method-of-moments procedure separately from others. However, it is still useful to understand which moments are most important for which parameters.

the result of differences in event severity and differences in event damage and are therefore informative about the effectiveness of adaptation capital, θ.[45,46]

3.5 Federal policy

Parameter ψ is the fraction of total damage covered by FEMA aid. We calibrate ψ from the subset of cyclones and storms that are included in the NOAA data plotted in Figure 2. We set ψ equal to the average ratio of FEMA aid to total NOAA damage from 2004-2016. This process yields $\psi = 0.11$, implying that federal aid covers 11 percent of the damage from an extreme weather event.

Parameter λ is the marginal cost of providing insurance. This costs creates a wedge between the actuarially fair insurance premium and the premium agents pay. If $\lambda = 0$, then the insurance premium equals the actuarially fair value and each local planner would choose full insurance to perfectly smooth consumption. We choose λ so that the ratio of insured losses relative to total damage in the model matches that in the data.

To calculate the ratio of insured losses relative to total damage, we use data on insured losses and the NOAA damage estimates. Event-level data on federally insured losses through the National Flood Insurance Program (NFIP) is available from fema.gov for all flooding events with \$1,500 or more in paid losses. Data on privately insured losses (e.g. through homeowners' insurance policies) is available for most tropical cyclones. These data are from estimates reported in NOAA's tropical cyclone reports for each individual storm and from

[45]One other possibility is that FEMA is subject to a county-specific "donor fatigue," and thus provides less aid in counties that more frequently declare disasters, severity held constant. However, we are not aware of any empirical evidence to support this hypothesis. Furthermore, as a government organization, FEMA is less likely than individual households to exhibit behavioral responses to charitable giving, such as donor fatigue. FEMA's mission is to "support our citizens and first responders to ensure that as a nation we work together to build, sustain, and improve our capability to prepare for, protect against, respond to, recover from and mitigate all hazards." (www.dhs.gov/disasters-overview). This mission statement is independent of how many disasters a locality has previously experienced.

[46]We drop extreme outliers from the calculations in Sections 3.4. We use two criteria to define extreme outliers: (1) county-years in which FEMA aid exceeds half of county income and (2) counties for which average FEMA aid for cyclones is over 500 times or is less than 1/500 times the value for non-cyclones. Fewer than 0.5 percent of all county-year observations with PDD events fall in one of these two categories.

the Insurance Information Institute.[47] We calculate the average ratio of total insured losses to total NOAA damage for all cyclones and for the subset of non-cyclone events that are included in the NOAA and NFIP data. The average value of this ratio from 2004-2016 is 0.42.

Finally, to calibrate the adaptation subsidy, we use information on federal funding for adaptation investment. One major source of funding is Hazard Mitigation Assistance (HMA) administered by FEMA. There are five separate HMA programs that provide support for adaptation: (1) Repetitive Flood Claims (RFC), (2) Severe Repetitive Loss (SRL), (3) Flood Mitigation Assistance (FMA), (4) Pre-Disaster Mitigation (PDM) and (5) Hazard Mitigation Grant Program (HMGP). We include all expenditures that fund capital investment to reduce damage from storms.[48] The second major source of federal adaptation funding is the US Army Corps of Engineers (USACE). We include all construction and maintenance expenditures from the USACE civil works budget that primarily relate to flood control.[49]

We measure the federal subsidy for adaptation in each year as the sum of the relevant HMA and USACE expenditures discussed above. We choose the size of the subsidy, s, to target total adaptation expenditures relative to GDP in the US. Complete data on HMA programs RFC and SRL is only available from 2008-2016. Therefore we target the average value of adaptation expenditures relative to GDP from 2008-2016.[50]

[47] See https://www.iii.org/fact-statistic/hurricanes#Estimated Insured Losses For The Top 10 Historical Hurricanes Based On Current Exposures (1). Data on insured losses is not available for the following tropical cyclones: Dolly, Earl, Matthew, and Hermine.

[48] Examples of expenditures we include are: the relocation or elevation of structures, flood-proofing of structures, shoreline stabilization, and storm water management. Examples of expenditures we exclude are: hazard mitigation plans, feasibility studies, salaries and property acquisition.

[49] Complete USACE budget reports are available from www.usace.army.mil/Missions/Civil-Works/Budget/. We include a construction or maintenance expenditure in our total if the project type (also labeled business line depending on the year) code relates to flooding. The 2015 budget does not separately report maintenance from operation and maintenance. We multiply operation and maintenance in 2015 by the average of maintenance expenditures as a fraction of total operation and maintenance expenditures in the other years. The 2008 and 2009 budgets do not include an operation and maintenance expenditure category. Our values of USACE expenditures for these years thus only include the construction category.

[50] In 2009, the USACE included a large emergency measure to fund the construction of flood barriers surrounding New Orleans. Such expenditures are atypical and make year 2009 an strong outlier. We exclude 2009 from the average.

Table 3 reports the value of the moments we target in the model and their corresponding values in the data. Overall, the model fits these targets quite closely.

Table 3: Model Fit

Moment	Model	Target
I/Y	0.255	0.255
K/Y	2.7	2.7
(HMA+USACE)/Y	6.65e-5	6.66e-5
Ω_h/Ω_l	1.52	1.52
$[FEMA/Y]_l$	0.0019	0.0019
$[FEMA/Y]_h$	0.0025	0.0025
X/D	0.46	0.42

The extreme weather events in the model are distinct from the literature on rare disasters and catastrophes. In particular, extreme weather events are much more frequent, occurring once every four years on average, and much less severe, destroying less than one percent of the capital stock. In contrast, the rare disasters modeled in Barro (2006) have an annual probability of 1.5-2 percent and destroy 15-64 percent of GDP, while the catastrophes modeled in Pindyck and Wang (2013) have an annual probability 0f 0.6-9 percent and destroy 10-20 percent of the capital stock.

4 Model results

We use our calibrated model to quantify the proportion of adaptation capital and its effect on average damage. We run two counterfactual experiments. In the first experiment, we quantify the effects of FEMA aid and adaptation subsidies on adaptation, average damage, and welfare. In the second experiment, we quantify the effects of adaptation on the welfare costs of climate change. We report the results for the low- and high-risk regions and for the aggregate US economy. To calculate the aggregate values, we weight the values in the low- and high-risk regions by their relative shares of US GDP, 0.46 and 0.54, respectively.

4.1 Quantifying adaptation

Figure 3 plots adaptation capital as a percent of the total capital stock in the low- and high-risk regions and for the aggregate economy. Localities in the low-risk region do not invest in adaptation capital. The expected benefit of adaptation investment is primarily determined by the probability of an extreme weather event p_i, and its severity, Ω_i. In low-risk localities, extreme weather events are rare, $p_l = 0.17$, and destroy only 0.62 percent of the capital stock when they occur, $\Omega_l = 0.0062$. Combined, the low values for both the probability and severity of extreme weather imply that the expected marginal benefit of adaptation investment never exceeds the marginal cost, and thus low-risk localities do not invest in adaptation capital.

In contrast, adaptation capital is 0.24 percent of the total capital stock in the high-risk localities. The probability and severity of extreme weather events are much larger in the high-risk localities, $p_h = 0.38$ and $\Omega_h = 0.0094$, leading to larger benefits from adaptation investment. In the aggregate US economy, adaptation capital represents 0.13 percent of the total capital stock. The total value of the US capital stock in 2016 was approximately 56.7 trillion in 2016 dollars, implying that US adaptation capital is approximately 75 billion in 2016 dollars.[51]

Adaptation capital is small relative to the total capital stock. However, the denominator of the total capital stock is somewhat miss-leading. The amount of capital damaged by extreme weather is only 0.23 percent of the total US capital stock. Adaptation capital equals 56 percent of the total capital destroyed by extreme weather. Thus, the amount of capital the US dedicates to reductions in extreme weather damage is over half of the total capital destroyed by extreme weather each year.

[51]Data on the capital stock are from: www.fred.stlouisfed.org.

Figure 3: Percent of Adaptation Capital

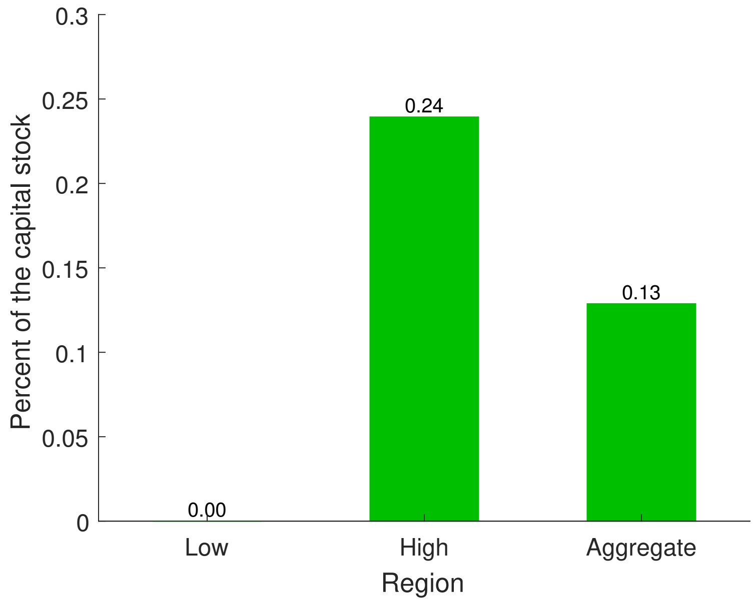
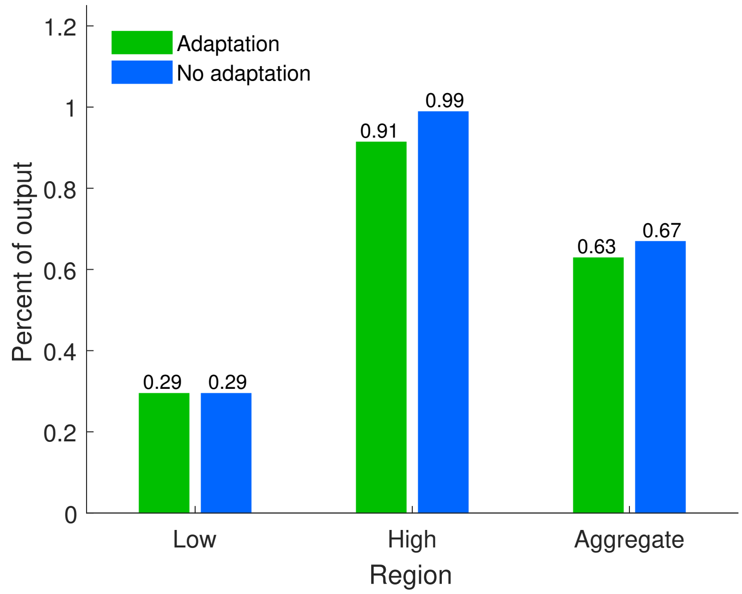


Figure 4 shows the effects of adaptation on the damage from extreme weather in the low- and high-risk regions and for the aggregate economy. The green bars plot the damage when the social planner in each locality optimally chooses adaptation investment. Damage is larger in the high-risk region than in the low-risk region because both the probability and severity of an extreme weather event are larger. The blue bars plot the damage when adaptation capital equals zero ($k^a_{ijt} = 0$) and all other variables equal their values in our baseline model.

Comparing the green and the blue bars reveals that adaptation reduces the damage from extreme weather by 7.6 percent in the high-risk region and by 6.0 percent in the aggregate economy. Adaptation has no effect on damage in the low-risk localities, because the low-risk localities choose not to adapt. Scaling the aggregate results by 2016 US GDP implies that the US avoids 7.5 billion (in 2016 dollars) each year because of adaptation.

Figure 4: Damage From Extreme Weather



4.2 Effects of federal policy on adaptation

The provision of FEMA aid for disaster relief decreases the damage a locality experiences from extreme weather, reducing its incentives to invest in adaptation capital. Federal subsidies for adaptation mitigate this moral hazard effect by increasing investment in adaptation capital. To quantify these effects of federal policy, we solve for an "aid-only" counterfactual stationary equilibrium and a "no-policy" counterfactual stationary equilibrium. In the aid-only equilibrium, we set the adaptation subsidy equal to zero ($s = 0$) and in the no-policy equilibrium, we set both FEMA aid and adaptation subsidies equal to zero ($\psi = s = 0$). Table 4 reports the main results.

Table 4: Effects of federal policy on adaptation

	No policy ($\psi = s = 0$)	Aid only ($\psi > 0,\ s = 0$)	Baseline ($\psi > 0,\ s > 0$)
Adaptation capital (percent of total capital stock)	0.04	0.00	0.13
Average damage (percent of output)	0.66	0.67	0.63

Moving from left to right on Table 4, we start with no policy and then add back each element of federal policy one at a time, beginning with FEMA aid and following with the subsidy. We compare the no-policy and aid-only equilibria (second and third columns of Table 4) to quantify the moral hazard effects of FEMA aid. We compare the baseline equilibrium with each of these counterfactual equilbria to quantify how much the subsidy offsets the moral hazard effects.

FEMA aid decreases the damage a locality experiences from extreme weather, reducing its incentives to invest in adaptation capital. In the no-policy equilibrium, adaptation capital is 0.04 percent of the total capital stock. The addition of FEMA aid (aid-only equilibrium) eliminates all investment in adaptation, reducing the level of adaptation capital to zero. This decrease in adaptation implies that the provision of FEMA aid increases average damage by 1.5 percent, from 0.66 in the no-policy equilibrium to 0.67 in the aid-only equilibrium. Scaling these effects by 2016 US GDP, implies that damage from extreme weather is almost 2 billion higher in 2016 dollars as a result of FEMA aid. To put this result in perspective, storm-related FEMA aid averages 6.7 billion per year. Thus, the increase in damage from moral hazard is over one quarter of the total FEMA aid each year, suggesting large moral hazard consequences from FEMA aid.

The federal subsidy for adaptation is designed to mitigate the moral hazard effects by reducing the relative price of adaptation investment. Indeed, the addition of the subsidy increases adaptation capital from 0 in the aid-only equilibrium to 0.13 percent of the capital stock in the baseline. Furthermore, the value of adaptation in the baseline exceeds its value in the no-policy equilibrium (0.13 compared to 0.04), implying that the subsidy more than offsets the moral-hazard effects of FEMA aid.

To measure the welfare effects of federal disaster policy, we use the consumption equivalent variation (CEV). The CEV is the percent increase in consumption an agent would need in every period in the baseline so that she is indifferent between the baseline and the counterfactual equilibrium. A negative value of the CEV indicates that expected welfare is higher in the baseline, which includes both components of federal disaster policy, then in the counterfactual which does not include all components of federal disaster policy. Thus, negative values indicate that federal disaster policy makes agents *better* off, while positive values indicate that federal disaster policy makes agents *worse* off. Table 5 reports the CEV for no-policy and aid-only counterfactuals in each region and in the aggregate economy.

Table 5: Welfare Effects of Federal Policy (CEV)

	Low risk	High risk	Aggregate
No policy ($\psi = s = 0$)	0.043	-0.071	-0.019
Aid only ($s = 0$)	0.002	-0.033	-0.017

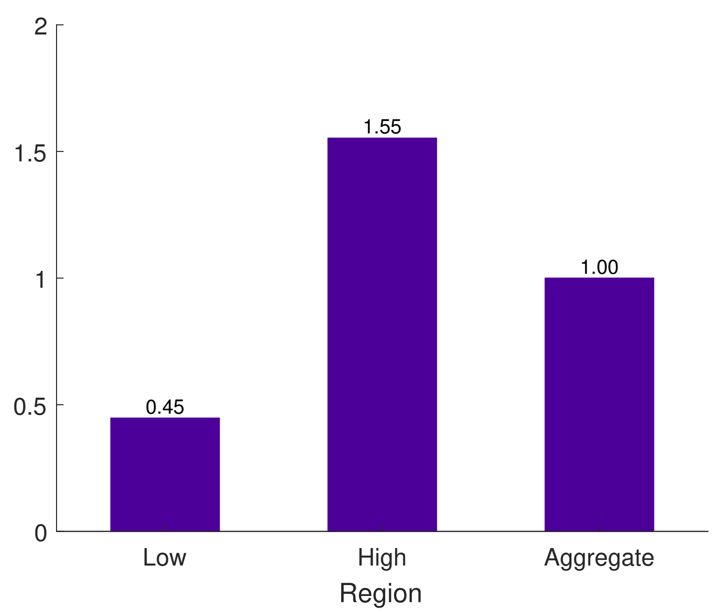
To understand the welfare consequences of federal disaster policy for the aggregate economy, we need to understand how the no-policy counterfactual compares to the social optimum. The only inefficiency in the no-policy counterfactual is that markets are incomplete. A federal social planner would like to allocate resources to perfectly smooth consumption in each locality, eliminating the idiosyncratic risk generated by the extreme weather shocks. The provision of FEMA aid removes some of that risk, by taxing all localities and returning the revenue to the localities that experience extreme weather. In isolation, this reduction in risk moves the economy closer to the social optimum, generating welfare benefits.

However, the provision of FEMA aid also introduces a distortion into the economy; the locality only internalizes the fraction $1 - \psi$ of damage not covered by the FEMA aid when it makes its adaptation decision. To correct for the FEMA-aid distortion, the federal government introduces a second, offsetting distortion, the adaptation subsidy. The locality's first order condition for adaptation capital, equation (4), reveals that the adaptation subsidy will perfectly correct the FEMA-aid distortion when $(1 - \psi)(1 + s) = 1$. In the model calibration, $(1 - \psi)(1 + s) = 1.12$, implying that the adaptation subsidy it too large relative to the level of FEMA aid. Thus, even though federal disaster policy is designed to introduce off-setting distortions into the economy, the distortions do not perfectly offset.

The CEV for the aggregate economy is negative, implying a small welfare gain from federal disaster policy; the welfare benefits from the consumption-smoothing provided by the FEMA aid dominate the distortion costs of the FEMA aid and the adaptation subsidy. Comparing the no-policy counterfactual to the aid-only counterfactual, we see that localities prefer the aid-only counterfactual (the magnitude of the aid-only CEV is lower). This comparison implies that the welfare benefits from the FEMA aid are larger than its distortion costs.

Federal disaster policy has opposite welfare-implications for localities in the high- and low-risk regions. The main reason for this difference is that federal disaster policy transfers resources from the low-risk region to the high-risk region. Figure 5 plots average policy receipts relative to taxes. If this ratio equals unity, then expected receipts equal tax payments, implying no transfers across regions. A value less than unity indicates that the average locality makes transfers. Similarly, a value greater than unity indicates that the average locality receives transfers. Receipts are 45 percent of total tax payments in the low-risk region and are 155 percent of total tax payments in the high-risk region, implying substantial transfers from the low- to high-risk regions.

Figure 5: Average Federal Disaster Policy Receipts Relative to Tax Payments



In the low-risk localities, the welfare-cost from the regional transfers dominates any welfare benefits from the FEMA aid. The CEV for both counterfactuals is greater than zero, implying that federal disaster policy makes low-risk localities worse off. The high-risk localities benefit from both the regional transfers and from the FEMA aid. The CEVs for both counterfactuals are negative, implying that federal disaster policy makes high-risk localities better off. In both the low- and high-risk regions, the CEVs have the largest magnitude for the no-policy counterfactual. This counterfactual leads to the biggest change in the regional transfers, which drives the within-region welfare implications of federal disaster policy.

4.3 Effects of climate change

We analyze the interactions between adaptation investment and climate change. Scientific models predict that climate change will substantially increase the intensity and damage potential of cyclones and other severe storms. In particular, Villarini and Vecchi (2013) use CIMP5 models to simulate the increase in the power dissipation index (PDI) for different climate change scenarios. The PDI is an index that incorporates storm duration, frequency, and intensity. Their projections imply that the PDI of Atlantic basin cyclones is likely to increase by 50-100 percent by 2100, depending on time path of atmospheric CO_2.[52] Additionally, Villarini and Vecchi (2012) argue that tropical cyclone frequency is not projected to change significantly over the 21st century, regardless of the climate change scenario. Thus, the projected increase in PDI indicates an increase in storm intensity and severity.

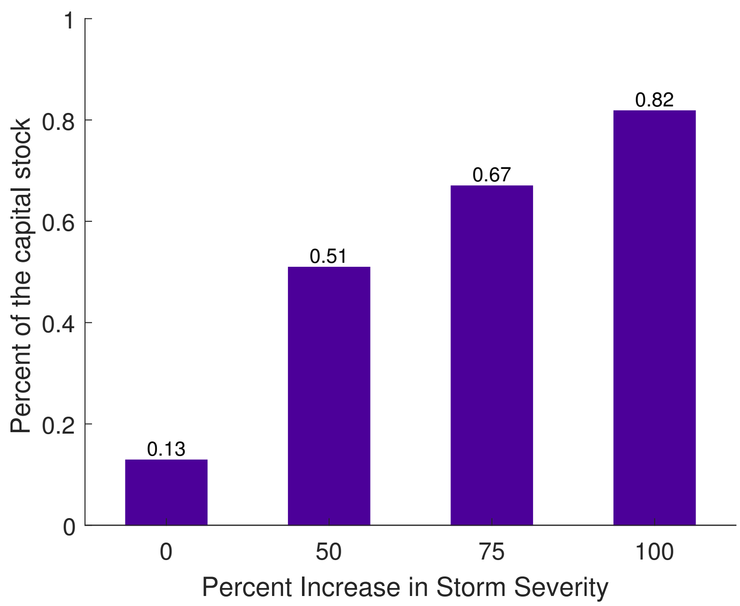
Based on this evidence, we define a climate change stationary equilibrium as our baseline model with a larger severity parameter, $\Omega_i^{cc} = \mu \times \Omega_i^{baseline}$. Scale-factor $\mu > 1$ represents the climate-change induced increase in storm severity. We consider three climate change scenarios, represented by $\mu = 1.5$, $\mu = 1.75$, and $\mu = 2$. For each climate change scenario, we calculate two climate change equilibria. In the first climate change equilibrium, agents opti-

[52]Specifically, Villarini and Vecchi (2013)'s results imply that a doubling of atmospheric CO_2 by 2100 will likely increase the PDI of Atlantic basin cyclones by 50 percent and that a quadrupling of atmospheric CO_2 by 2100 will likely increase the PDI by 100 percent.

mally choose adaptation capital, like they do in the baseline. In the second climate change equilibrium, we force the adaptation policy function to equal its value in the baseline. Thus, localities cannot adjust their adaptation decision rule in response to climate change. We refer to these two equilibria as the adaptation and no-adaptation climate change equilibria, respectively.

Figure 6 plots aggregate adaptation capital in the baseline (zero percent increase in severity) and in each adaptation climate-change equilibria (50, 75 and 100 percent increases in severity). Even with the most optimistic climate change projections (50 percent increase in severity) adaptation capital is more than triple its value in the baseline.

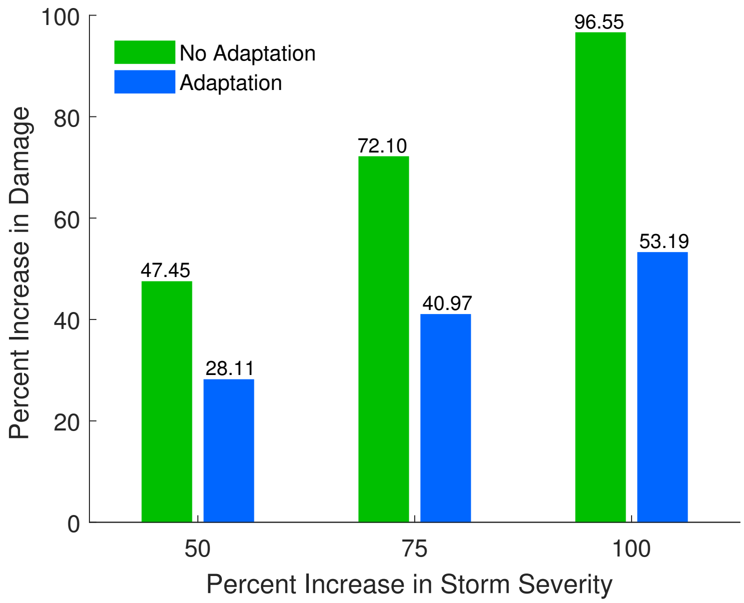
Figure 6: Adaptation Capital: Climate Change Equilibria With Adaptation



This adaptation investment reduces the increase in damage the localities experience as a result of climate change. Figure 7 plots the effects of climate change and adaptation on average damage. Specifically, for each climate change scenario, the green and blue bars plot the percent increase in average damage from the baseline in the no-adaptation and adaptation climate change equilibria, respectively. In the no-adaptation equilibria, average damage is approximately μ times the value of damage in the baseline; since agents cannot adapt, they cannot mitigate the increase in extreme weather severity. As a result, average damage increases by almost the same scale-factor as the storm severity.[53]

When agents can adapt, average damage increases by considerably less than the increase in severity. For example, the ability to adapt implies that a 50 percent increase in severity leads to an increase in average damage of approximately 28 percent, instead of 47 percent. Looking across all three scenarios, adaptation reduces the increase in average damage as a result of climate change by approximately 45 percent.

Figure 7: Percent Increase in Average Damage From the Baseline



While the reductions in damage from adaptation are considerable, there are diminishing returns to adaptation. To quantify these diminishing returns, Table 6 reports the average elasticity of damage with respect to adaptation capital for each climate change scenario. The elasticity is the percent difference in damage between the adaptation and no-adaptation climate change equilibria, divided by the percent difference in adaptation capital. Across all three climate change scenarios, the elasticity is negative, implying that damage decreases with adaptation investment. However, the magnitude of the elasticity is larger when climate change is less severe (smaller μ) and hence adaptation capital is smaller.

[53]The damage is slightly less than μ times the baseline value because climate change decreases the expected marginal product of productive capital, reducing incentives for productive capital investment. All else constant, less productive capital reduces the realized damage because there is less for the storm to destroy.

Table 6: Elasticity of Damage With Respect to Adaptation Capital

$\mu = 1.5$	$\mu = 1.75$	$\mu = 2$
-4.9	-4.6	-4.3

To measure the welfare effects of climate change, we again use the consumption equivalent variation (CEV). The CEV measures the percent increase in consumption an agent would need in every period in the baseline such that she is indifferent between the baseline and the climate change equilibrium. Table 7 reports the CEV in the adaptation and no adaptation equilibria for each climate change scenario. All values of the CEV are negative, indicating that climate change makes agents worse off. Furthermore, the magnitude of the CEV increases considerably with the climate change scenario, from -0.41 percent when $\mu = 1.5$ to -0.82 percent when $\mu = 2$.

Finally comparing the CEVs across the adaptation and no-adaptation climate change equilibria, we see that adaptation reduces the welfare cost of climate change. For example, when $\mu = 1.75$, the CEV is -0.76 when agents cannot adapt, but only -0.62 when agents can adapt. Looking across all three scenarios, we find that adaptation reduces the welfare cost by 15-20 percent.

Table 7: Welfare Effects of Climate Change (CEV)

	$\mu = 1.5$	$\mu = 1.75$	$\mu = 2$
Adaptation	-0.41	-0.62	-0.82
No Adaptation	-0.53	-0.76	-1.00

5 Conclusion

We develop a structural macroeconomic model to quantify the links between adaptation, federal disaster policy, and climate change. The framework is a dynamic general equilibrium model in which heterogeneous localities experience idiosyncratic extreme weather shocks that damage their capital stocks. A social planner in each locality can invest in adaptation capital to reduce the damage from extreme weather and can purchase insurance to partially smooth consumption.

We calibrate the model and use it to quantify the amount and effectiveness of adaptation capital. We find that in localities with a high risk of extreme weather, adaptation capital is approximately 0.24 percent of the capital stock and reduces the damage from extreme weather by 7.5 percent.

We use our calibrated model to evaluate federal disaster policy. We find that the provision of FEMA aid alone reduces adaptation capital to zero, implying a large moral hazard effect. The federal subsidy for adaptation more than offsets the moral hazard effects of FEMA aid; the net effect of both FEMA aid and subsidy more than doubles adaptation capital from its value in the counterfactual equilibrium with no federal policy.

Federal disaster policy generates a small welfare gain for the aggregate economy; the welfare benefits from the consumption-smoothing provided by the FEMA aid dominate the welfare costs of the additional distortions created by the FEMA aid and the adaptation subsidy. However, these welfare gains are not equally distributed across the high- and low-risk regions. Federal disaster policy generates substantial transfers from low- to high-risk localities, making the low-risk localities worse off and the high-risk localities better off.

Finally, we quantify the interaction between adaptation and climate change (modeled as a permanent increase in extreme weather severity). Our results reveal that adaptation has the potential to substantially reduce the damage from climate change and the associated welfare cost. However, adaptation is characterized by diminishing returns. As the severity of climate change increases, the ability of adaptation to reduce the accompanying damage falls.

Our analysis focuses on carefully quantifying the effects of federal disaster policy and climate change on adaptation capital. Of course, capital investment is only one of several ways that agents can adapt to reduce the welfare cost of extreme weather. In ongoing work, we explore the effects of climate change and federal disaster policy on migration, a second type of adaptation.

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