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Essays on Environmental and Financial Economics

by

Yulei He

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Agricultural and Resource Economics

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor James Sallee, Chair
Professor Lucas Davis
Professor Joseph Shapiro

Spring 2022

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Abstract

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Doctor of Philosophy in Agricultural and Resource Economics

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Professor James Sallee, Chair

Climate change may influence financial market participants in many ways. Particularly, in a market with financial frictions, real estate usually serves explicitly or implicitly as a collateral in debt financing. Risks of physical damage to real property resulting from climate hazards and sea level rise may bring about not only direct loss, but also credit constraint for property holders. How much agents are affected by climate risks is an important research question, and has been explored substantially in the burgeoning climate risk literature. Another important question is what actions can be taken to manage or reduce the risks, and how to evaluate those efforts, which is the main goal of this dissertation.

The first chapter studies the effectiveness and efficiency of adaptation investments for averting property damage (e.g. defensible space, drainage system, shoreline stabilization, etc.). Using variation in grant availability for adaptation projects through a U.S. federal program as a quasi-experiment, I quantify the impacts of property-related adaptation investments on debt financing of local governments and the real estate sector. There are three main findings. First, following adaptation investments, the average borrowing cost of a county government decreases by 10-26 basis points for 20 years. Second, nationally, adaptation investments have an insignificant effect on outstanding debt, while in the South and Northeast debt falls by 4.2%. Third, an average investment has a project cost of $2 million and reduces property damage by $323,000 per year, which implies a 15-year internal rate of return of 19%. Overall, these results suggest that adaptation mitigates climate risks. Additional calculations reveal that current levels of adaptation are below the social optimum; and given current spending, capital could be allocated more efficiently by altering the distribution across regions.

The second chapter leverages tools in natural language processing (NLP) to explore the potential of generating large-scale yet granular measurements of how individuals perceive climate change and actions for addressing climate challenges. Social media such as Twitter provide a platform for users with diverse backgrounds to freely share their opinions, and thus capture real-time, higher-dimensional information that is not reflected in standard opinion

surveys or polls. In this essay, I evaluate the use of different machine learning models to classify opinions on climate change and related actions from tweets. For model training, I annotate a dataset of climate-related tweets using a multi-stage system that distinguishes between two types of climate actions, mitigation or adaptation. I show that a deep learning approach based on contextual embeddings (BERT) outperforms traditional models, and addressing unbalanced classes through up-sampling achieves additional gains in accuracy. Finally, I discuss the limitations and potential applications of text-based characterization of opinions on climate change actions.

To Huiling Cai

for her unconditional love and unwavering support.

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Acknowledgments

I am deeply grateful to James Sallee for his guidance and encouragement since the very beginning of my life in graduate school. I have also learned so much from every conversation I have had with Lucas Davis and will never forget the wisdom he has shared about how to conduct great research. Additionally, I would like to thank Joseph Shapiro for being an incredible mentor and exemplar. His ingenious ways of thinking and his own work have completely reshaped my research style. Furthermore, I highly appreciate the presence of Catherine Wolfram, Meredith Fowlie, and Sofia Villas-Boas throughout my intellectual development. They are the best role models of women in academia. There are many other Berkeley faculty members who are not listed here yet provided invaluable advice. The nurturing and supportive academic environment of Berkeley, from my perspective, is incomparable to any other place in the world.

In addition to those much cherished advisors, my fellow doctoral students have been the most valuable assets during my intellectual journey. I would not have gotten through all the ups and downs of doctoral study without their camaraderie. It is also crucial for me to thank the entire ARE community, especially the staff, alumni, and several mentors from UC Davis, for their immense kindness and generous help. The Fisher Center for Real Estate and Urban Economics, the Berkeley Food Institute, and the Sacheti Family Fellowship provided important financial support. And most of all, I could not have become who I am today without my dedicated, caring, and thoughtful family.

Lastly, I want to express my gratitude for being able to live in a society and an era in which I enjoy substantial freedom of pursuing independence and fulfillment as a human being. I had taken this for granted for a long time, but the more I learn about the world, the more I realize that this is both a fortune and an endeavor of many, both living and dead, of which I will become a part.

Chapter 1

Adaptation Investments, Property Damage and Debt Financing of Local Governments

1.1 Introduction

Climate change brings about physical damage to real property through sea level rise and increased frequency and severity of extreme weather events (TCFD 2017; IPCC 2021). For instance, about 60,000 structures were destroyed by wildfires in the U.S. within the past five years (Headwaters Economics 2020). According to a recent study, nearly one-third of U.S. homes are at high risk of natural disaster (CoreLogic 2021). While property itself is an important component of welfare, the fact that real estate usually serves explicitly or implicitly as a collateral in debt financing implies that damage to real property can further undermine the capacity of agents to make new investment to address climate challenges. Local governments are particularly at risk. Individuals can move away from rising risks, but municipal boundaries are fixed. Moreover, the creditworthiness of local governments is tied directly to the health of the local real estate market, which is monitored closely by rating agencies and investors because it represents the financial base of local government (S&P Global 2019).

Fortunately, it is possible to mitigate these risks. Insurance is one typical option to avert loss in property value from a negative shock. However, the non-diversifiable nature of climate risks poses doubts about whether an insurance market can sustain its operation (Rothschild and Stiglitz 1976; Cummins 2006). Adaptation, or adjusting buildings and their surrounding environments to improve resilience, is another option that receives growing attention. For example, this year, Florida just committed $640 million to invest in resilience efforts (Office of Governor Ron DeSantis 2021). However, so far there is limited empirical evidence on the effectiveness of such investments in averting damage and improving financial positions, as well as discussion of how we should assess whether such investments are at efficient level.

This paper empirically examines how property-related adaptation investments affect debt financing of local governments and the real estate sector using administrative data and variation generated by a large U.S. federal grant program. By comparing outcomes in adapted and non-adapted counties following investments and controlling for lagged disaster effects, this research reveals that property-related adaptation investments are indeed effective in mitigating climate risks, but far from being at efficient level today.

The program studied in this paper, Hazard Mitigation Assistance Grants, is the primary source of federal funding targeting local adaptation. Initially established by Federal Emergency Management Agency (FEMA) in 1989, Hazard Mitigation Assistance Grants provide funding for local governments to "reduce or eliminate long-term risk to people and property from future disasters", and under the Stafford Act, allocate the majority of funds as certain percentage of total assistance to a state after a Presidential Disaster Declaration (PDD). Typical adaptation projects include elevating, relocating and retrofitting public and private structures, shoreline stabilization, vegetation management, infrastructure protective measure, and so on. Up to 2018, 83% of cumulative amount of property-related adaptation investments and 80% of projects funded by these grants are associated with hurricanes, floods and storms. I compile a county-level data set by linking administrative data on adaptation projects from FEMA to information on interest payments and outstanding debt from the Census of Governments and Annual Survey of State and Local Government Finances.

To obtain quasi-experimental estimates of the impacts of property-related adaptation investments, I apply a modified difference-in-differences research design to address endogeneity in investment decisions and test its validity in various ways. While a local government can have continual demand for adaptation over time, using any source of funding, typically municipal debt, there is a surge in federal grants right after disaster incidents that drives new investments. Panel variation in the timing and location of these federal grants and adaptation investments allows me to flexibly control for unobservables that are time-invariant in a county and unobserved common shocks in a period. In addition, there is a discrete change in grant availability at the state level stemming from the funding rule that is linked to declared major disasters. The state then decides which county's proposed adaptation projects get funded according to a priority list. These program features imply that the exact timing of adaptation investments at the county level are largely driven by exogenous factors. Finally, counties in and outside declared disaster areas are all eligible for the grants, making it possible to control for other long-term residual effects of disasters such as post-disaster reconstruction activities. I test the validity of this research design using event study analysis, different approaches to control for disaster effects, specifications separating out "pure" adaptation effects in non-disaster areas, and sensitivity analyses with alternative specifications, which generally yield supportive evidence.

I show that over the 1989–2018 period, following a year in which adaption investments occur, the average borrowing cost of a county government decreases by 10-26 basis points (1.7-4.4% of the mean) in the first 20 years. This effect has economically large magnitude, as previous studies find that a moderate increase in climate risk exposure is associated with an increase of 5-23 basis points in borrowing costs (Painter 2020; Goldsmith-Pinkham et al. 2021; Jerch, Kahn, and Lin 2021). Meanwhile, there is a statistically insignificant decrease in outstanding debt following adaptation investments.

Since it is conjectured that these effects are driven by the collateral channel, or increase in capital value in the community resulting from lower risks that future disasters will damage property, I conduct complementary analysis of the impacts of adaptation investments on the local real estate sector. I find that new adaptation investments lead to an average decrease of $323,000 in property damage per year in the first 15 years. Given an average project cost of $2 million and the estimated annual averted property damage, the implied 15-year internal rate of return (IRR) of an adaptation investment is about 19%, which is substantial compared to the typical financing cost. Changes in average home value are small and statistically insignificant. Nevertheless, there is a significant and enduring increase in construction of new homes.

The paper also investigates difference in effects of adaptation investments across regions. Theoretically, society's welfare will be maximized when funds for adaptation investments are allocated in a way such that the marginal returns are equalized over regions. In contrast, I find that the effects of adaptation investments on all outcomes are strongest for counties in the South and Northeast. While decrease in borrowing costs in the South and Northeast is consistently substantial, the West and Midwest see smaller and insignificant effects. The estimated decrease in outstanding debt is again only significant in the South and Northeast, reaching $4.7 million, equivalent to a 4.2% decrease from the mean. Similarly, property damage reduction in the South and Northeast is greater, resulting in an implied 15-year IRR of 45%.

The findings in this article suggest that property-related adaptation can be an effective approach to address challenges of climate risks by reducing direct property damages and improving financial conditions of economic entities. Even though the influences of climate risks on financial markets are multifold and complex, there is little doubt that physical harms to real estate plays a central role, as it is the collateral or underlying of a range of assets (Giglio, Kelly, and Stroebel 2021). Nonetheless, these harms are not entirely unavoidable. By investing in adaptation, the negative consequences of climate risks can be substantially, if not fully, averted. With increased frequency and severity of extreme weather events, the expected benefits of adaptation will be even higher in the future.

However, the strikingly high empirical estimates of returns to property-related adaptation investments based on averted damage suggests that the current level of investment is too low. In fact, the overall return could be even higher as this simple IRR only monetarizes one specific benefit and leaves out broader benefits such as savings from less interest payment and protection of human life. Given the relatively low-cost, implicitly subsidized municipal debt in the U.S., the large IRR indicates that increasing local governments' spending on adaptation would be socially beneficial.

This paper is related to the recent, emerging literature on how financial markets respond to threats of climate change, and in particular the real estate and the municipal debt market (Bernstein, Gustafson, and Lewis 2019; Baldauf, Garlappi, and Yannelis 2020; Keys and Mulder 2020; Kousky, Palim, and Pan 2020; Murfin and Spiegel 2020; Painter 2020; Goldsmith-Pinkham et al. 2021; Issler et al. 2021; Jerch, Kahn, and Lin 2021; Ouazad and Kahn 2021). Most empirical studies in this realm focus on finding measurements for climate risks and using exogenous variation in risk level or in exposure to risk to estimate its impacts on financial outcomes such as home values and bond yields. Nonetheless, these studies pay little attention to the role of adaptation in mitigating risks, which is assumed to be a passive process and implicitly incorporated into the response of economic agents. My paper departs from the literature by emphasizing adaptation instead of risk exposure as the treatment of interest, and providing the first quasi-experimental estimates of the effects of existing adaptation investments induced by targeted grants on financial outcomes.

In addition, this research contributes to the literature on adaptation to climate change (see Kahn (2016) and Fankhauser (2017) for a comprehensive review). Much of the prior literature centered around small-scale, private adaptation such as irrigation, air conditioning and floor elevation (Hornbeck and Keskin 2014; Barreca et al. 2016; Wagner 2021). Besides, empirical studies about adaptation typically quantify the impacts and cost-effectiveness of adaptation measures, and their heterogeneity over time, across space, or among different demographic groups. This paper instead focuses on adaptation activities of local governments and related to the real estate sector, and seeks to quantify both direct averting effects and broader impacts on financing capacity. It is related to and methodologically different from Fried (2021), which quantify averted damage through adaptation investments in a macroeconomic model and uses the same federal grant program for model calibration.

Another strand of related literature focuses on how natural disaster insurance or other assistance influence post-disaster recovery (Deryugina 2017; Kousky 2019; Gallagher, Hartley, and Rohlin 2021). While these cash transfers also improve outcomes of disaster-affected agents, they mitigate negative shocks essentially by spreading losses among agents rather than reducing the overall level of losses.

Finally, this paper contributes to the literature on finance and provision of local public goods. When the federal government disburses funds to local governments, it may follow rules that are not exactly aligned with maximizing returns of those funds. Recent empirical studies find considerable spatial misallocation in different infrastructure sectors, and use spatial industrial organization or quantitative trade models to quantify the extent of misallocation (Balboni 2019; Hsiao 2021). Since the effect of climate risks differ spatially and adaptation benefits are local, centralized distribution of adaptation funding may give rise to inefficiency in capital resource allocation. In this study, I show evidence of spatial misallocation by finding substantial heterogeneity in both actual adaptive effects and responses of the debt market to adaptation investments across regions.

A second possible inefficiency is in the level of public good provision. Samuelson (1954) posits that the efficient level of public good provision will be reached when the sum of marginal benefits is equal to the marginal cost of provision. Previous papers have studied investments in different types of public good in the U.S. such as highway (Allen and Arkolakis 2019) and school facility (Cellini, Ferreira, and Rothstein 2010). The benefit estimates are generally higher than the costs, and the implied returns are sizable, suggesting that the level of provision is far below the optimal. Infrastructure investments in developing countries are found to have even higher returns, but they are usually explained by substantial credit constraints and market integration effects (Duflo 2001; Donaldson 2018), which seem less applicable in developed countries. This article investigates a different type of public good in the context of a developed country and shows that it also has surprisingly high returns.

The paper proceeds as follows. Section 2 outlines the conceptual framework. Section 3 provides details of the institutional background and research design. Sections 4 and 5 describe the data and empirical strategy. Sections 6 presents and discusses the results. Section 7 concludes.

1.2 Conceptual Framework

Real estate as a pledgeable asset plays an important role in personal and household finance (Agarwal, Ben-David, and Yao 2015; Defusco 2018), entrepreneurial and corporate finance (Chaney, Sraer, and Thesmar 2012; Schmalz, Sraer, and Thesmar 2017) and municipal finance (Cestau et al. 2019). In the case of municipal finance, debt instruments are not directly ensured by assets. However, real estate still serves the collateral function implicitly, as municipal bonds are generally backed by government's power to tax property owners or by revenues from public projects that largely rely on demand from local residents.[1] In fact, many local governments face a constitutional or statutory debt limit as a percentage of total assessed valuation of taxable properties in the jurisdiction. Therefore, local governments could confront significant financial constraints if climate (or other) risks are deemed to put the health of the local real estate market in jeopardy. Indeed, climate risks are receiving

[1]General obligation bonds are backed by the "full faith and credit" of the issuer, which has the power to tax residents to pay bondholders. Revenue bonds are backed by revenue from a specific project or source, such as highway tolls or lease fees. (Investor.gov, https://www.investor.gov/introduction-investing/investing-basics/investment-products/bonds-or-fixed-income-products-0)

growing attention as a factor affecting municipal bond credit rating and financial capacity of local governments in the financial industry recently (BlackRock 2019; Moody's 2017; S&P Global 2017, 2019).

The Task Force on Climate-related Financial Disclosures (TCFD)[2] divides climate risks into two major categories: risks related to the transition to a lower-carbon economy (transition risks) and risks related to the physical impacts of climate change (physical risks), which can be further divided into extreme weather events such as cyclones, droughts, and wildfires, or longer-term shifts in climate patterns that may resulting in sea level rise or chronic heat waves (TCFD 2017). While most existing studies look at the impacts of sea level rise on the real estate sector, in this paper, I focus primarily on event-driven physical risks for several reasons. First, disaster incidents are more salient and likely to receive investor attention. Second, while studies about sea level rise generally reply on expected changes that have not yet been realized, disaster incidents happened in the past allow me to obtain credible ex-post estimates that can readily be incorporated into scenario analysis and simulation modeling. Third, there is a wider geographical coverage of disaster incidents and their implications are relevant for a large number of localities.

Although the consequences of climate risks could be devastating, it is possible to moderate them through adaptation. In general, adaptation is defined as "adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities" (IPCC 2007). This could take a variety of forms, including modifying consumer behaviors, adopting defensive technologies, redesigning production process, building infrastructure and migration (see Kahn (2016) and Fankhauser (2017) for a comprehensive review). Some studies examining adaptation also assume that any observed difference in the damage-exposure relationship among agents, across locations or over time is attributed to adaptation efforts (Hsiang and Narita 2012; Burke and Emerick 2016). While many adaptation measures can be adopted by individual households and firms, some will only be efficiently provided in a collective manner given their public good nature (Barrage 2020). Depending on scale, these activities would be undertaken by different levels of government. Local governments are suitable for median-scale projects whose influence is limited to local communities, such as improving sewage systems or developing defensible space for fire. If the impacts of adaptation activities potentially extend across multiple local jurisdictions, such as building large-scale levees and dams, then they should be undertaken by regional entities or the federal government.

An additional question to who should undertake adaptation is how to finance adaptation.

[2] Consisted of a group of executives from the finance industry, the Task Force on Climate-related Financial Disclosures (TCFD) was formed in 2015 to "make recommendations for consistent company disclosures that will help financial market participants understand their climate-related risks" by the Financial Stability Board, an international body established after the G20 London summit to monitor and make recommendations about the global financial system.

Absent substantial savings and external grants, large-scale adaptation projects, both public and private, are likely financed by debt, as they require sizable capital spending immediately, whereas the payoff stream stretches over many periods (BlackRock 2019). Green bonds, touted as a vehicle for financing climate actions, is a real-world example.[3] There are also numerous loan programs for financing building retrofits provided by both the government and the private market.[4] With external grants covering a portion of capital needed to finance adaptation, demand for debt will be reduced.

The Crow Creek Flood Control Project provides a real-world example of adaptation investments of local governments. Located in Tulsa, a county in the northwest of Oklahoma, the project included a new underground storm sewer system and a new rainwater detention site, which would help lower the flood risk for 62 homes in the Florence Park South neighborhood. The total development cost was $2.2 million, with $1.5 million financed through federal grants induced by a severe winter storm in December 2007, and $700,000 through funds from the stormwater utility fee.

A Simple Model of Property-Related Adaptation Investment of Local Government

I formalize the intuition of why a local government would want to invest in property-related adaptation, and how it interacts with debt financing, using a simple model adapted from Metcalf (1993). It develops a theory of supply of municipal debt based on the view that it is a tool for smoothing public spending intertemporally. I add property-related adaptation and disaster expenditure to the original model as modifiers of budget balance and borrowing rate of the local government. I also incorporate into the model potential sources of underinvestment such as moral hazard and behavioral bias in a parsimonious way.

Consider a community of N homogenous individuals living over two periods. These individuals obtain utility $U(C_1, C_2, G)$ from consuming a durable public good G and private goods C_1 and C_2 in each period. They earn lifetime income with present value of W, pay for the private good and pay lump-sum taxes T_1 and T_2 to the local government. Private savings in period 1 can earn an after-tax rate of return ρ. The private budget constraint is:

$$C_1 + T_1 + \frac{C_2 + T_2}{1 + \rho} = W \tag{1.1}$$

The local government is responsible for providing the public good G and investing in adaptation A in period 1. It can finance its expenditure using tax revenue NT_1 (the deadweight loss associated with taxing is ignored here) and debt B at a borrowing rate of r_m. A fraction

[3] "Columbia Issues First-Ever 'Green Bonds' to Fund Stormwater Improvements." https://www.columbiasc.net/headlines/12-07-2018/Green-Bonds

[4] https://betterbuildingssolutioncenter.energy.gov/financing-navigator

γ of adaptation investment is paid by external grants. Therefore, the government budget balance in period 1 is:

$$G + (1-\gamma)\,A = B + NT_1 \tag{1.2}$$

In period 2, the local government must use the tax revenue NT_2 to repay the debt, pay the interest, and incur exogenous expenditure on disaster D. A fraction α of disaster expenditure is paid by federal assistance. Disaster expenditure can be modified by adaptation in period 1 through a parameter $\widetilde{k}$. The tilde representation indicates that this can be a subjective evaluation of the effect of adaptation on mitigating disaster risk and gives room for behavioral bias. The government budget balance in period 2 is:

$$(1+r_m)\,B + (1-\alpha)\,D\left(1-\widetilde{k}A\right) = NT_2 \tag{1.3}$$

Finally, the borrowing rate is endogenous and depends on the ratio of amount of debt B to some measure of the ability to repay the debt in the future (assessed value of property, income, etc.), V, or, without a rigorous definition, the value of the collateral. V can be modified by disaster D through a parameter $\widetilde{p}$ and by adaptation A through a parameter $\widetilde{q}$. Similarly, the tilde representation captures subjective evaluation of the effects of disaster and adaptation on the collateral value. The function $\phi\,(.)\,,\ \phi' > 0$, captures the existence of capital market imperfections but does not microfound a specific type of financial friction. Formally:

$$r_m = \phi(\frac{B}{V(1-\widetilde{p}D)(1+\widetilde{q}A)}) \tag{1.4}$$

This formulation of borrowing rate suggests that conditional on the collateral value, the more the local government borrows, the higher the borrowing rate would be. Debt limit can be viewed as an upper bound of the debt to value ratio. Disasters destroy collateral value, whereas adaptation investments increase collateral value. Both affect debt limit and borrowing rate through collateral value.

The local planner's problem is to maximize $U(C_1, C_2, G)$ subject to constraints (1) – (4). With positive taxation in both periods and positive borrowing in period 1, combining the first-order conditions for taxation, borrowing and adaptation yields:

$$\underbrace{1+\phi+\frac{B}{V(1-\widetilde{p}D)(1+\widetilde{q}A)}\phi'}_{Marginal\ Cost\ of\ Borrowing} = \underbrace{\frac{\widetilde{k}\,(1-\alpha)\,D + \left(\frac{B}{V(1-\widetilde{p}D)(1+\widetilde{q}A)}\right)^2 V\,(1-\widetilde{p}D)\,\widetilde{q}\phi'}{1-\gamma}}_{Marginal\ Benefit\ of\ Adaptation}$$

This expression implies that the local government will invest in adaptation until the marginal cost of borrowing is equal to the marginal benefit of adaptation. There are three components in the marginal benefit of adaptation: savings from less disaster expenditure, $\widetilde{k}\,(1-\alpha)\,D$, savings from reduced borrowing cost, $\left(\frac{B}{V(1-\widetilde{p}D)(1+\widetilde{q}A)}\right)^2 V\,(1-\widetilde{p}D)\,\widetilde{q}\phi'$, and both are scaled by the fraction of own-source funding for adaptation investment, $1-\gamma$. α, $\widetilde{k}$, $\widetilde{p}$, $\widetilde{q}$ create different sources of deviation from the socially optimal level of adaptation investment, including moral hazard effects of federal disaster assistance and subsidized insurance, the local planner's and investors' misperception or inattention about the effects of disasters and adaptation investments.

The model also suggests that adaptation investment is in general an optimization problem and thus endogenous. To estimate the causal effects of adaptation investments, I make use of exogenous shocks to external grants for adaptation, which will drive up the marginal benefit and induce new investments.

1.3 Hazard Mitigation Assistance Grants

Several federal agencies established grant programs for supporting local adaptation, but FEMA's hazard mitigation assistance grants are the primary sources of funding (The White House 2014; CRS 2019; GAO 2021).[5] These grants target community-based adaptation and cover a wide range of adaptation activities and projects including elevating, relocating and retrofitting public and private structures, shoreline stabilization, vegetation management, infrastructure protective measure, mitigation planning, safe room construction, backup generator purchase, and so on.[6] Under the general categorization of hazard mitigation assistance, FEMA established three major grant programs:[7] the Hazard Mitigation Grant Program (HMGP), the Pre-Disaster Mitigation Program (PDM) and the Flood Mitigation Assistance Program (FMA).

Created in 1989 by the Stafford Act, HMGP is the first and largest hazard mitigation assistance grant program. The law stipulated that each HMGP grant should not exceed a ceiling (also known as "lock-in") calculated using a formula based on a percentage of the estimated total assistance to a PDD[8] and federal funds should be provided at a cost-share with other

[5]Other federal programs include HUD's Community Development Block Grant program, the Department of Commerce's Economic Development Administration grants, EPA's State Revolving Loan Funds, US Department of Agriculture's Rural Development grants, and US Army Corps of Engineers programs (The White House 2014). There are also state and local government grant programs for adaptation. For a full list of such programs, see https://toolkit.climate.gov/content/funding-opportunities.

[6]See FEMA (2015) for a complete list of eligible adaptation activities and projects.

[7]The total project cost between 1989-2018 under HMGP is $12.84 billion; under PDM $1.24 billion; under HMA $0.98 billion.

[8]FEMA has three types of presidential disaster declaration (PDD): Emergency Declaration (EM), Major Disaster Declaration (DR), and Fire Management Assistance Grant Declarations (FM). EM may be declared before an incident occurs to save lives and prevent loss, and the assistance is limited to individuals and households, not the public sector. FM happens at the beginning of or during a fire, as its goal is to provide

non-federal sources of funding (Section 404 of the Stafford Act, 42 U.S.C. 5170c).[9] States are major applicants of grants and interact directly with FEMA, while local governments are sub-applicants and submit their applications to the state.[10] States then determine which applications to submit to FEMA based on the amount of funding available and their priorities outlined in mitigation plans approved by FEMA.

PDM grants can be applied annually, with the total available amount depending on Congressional appropriations. FMA grants accept annual applications as well, but only NFIP-insured properties are eligible, and funding is available through the National Flood Insurance Fund.

Even though the research design described below base primarily on the program structure of HMGP, which is quite different from the requirements of PDM and FMA, I don't exclude grants from these two programs in the empirical analysis for the following reasons. For PDM, the actual year-to-year appropriations varied greatly and funds are awarded on a competitive basis, and therefore there is still a lot of uncertainty in when and which counties will get the grants even though they can actively choose the timing of applications regardless of disaster occurrence. For FMA, priority will be given to properties that suffer repetitive loss, which is implicitly linked to disaster incidents. In the sensitivity analysis, I show that there is little change in estimates of coefficients of interest by using only HMGP grants as the source of useful variation and treating PDM and FMA grants as controls.

Hazard Mitigation Assistance Grants as a Research Design

The empirical challenge to estimate the effects of adaptation investments is that there are likely unobserved factors that covary with adaptation investments and debt financing as well as real estate market outcomes. In general, investment is a strategic choice. Counties

federal assistance for suppression of fires "that might become a major disaster". DR happens after a disaster hit. A state is the unit of declaration, and the state governor decides whether to assemble a Preliminary Damage Assessment (PDA) team to compile a report and submit a request to the president. The cost of the disaster, or the amount of federal aid needed, is determined in the PDA report, although the number will be updated later. Per capita estimated eligible disaster cost is one of the most important indicators of whether the disaster is qualified as a major disaster.

[9]Both the cost-share and the formula used to determine the ceiling of a HMGP grant change over time. Between 1989 and 1993, the ceiling was 10 percent of granted public assistance for a disaster, and the cost share between federal and state government was 50-50. In 1993, the ceiling was increased to 15 percent and the basis for funding was extended from just public assistance grant expenditures to all grant expenditures (the sum of individual and public assistance), excepting administrative costs. The cost share between federal and state government also went to 75-25. In 2000, the ceiling was increased to 20 percent if the state has a FEMA-approved enhanced mitigation plan in place prior to the disaster. In 2003, the percentage was decrease to 7.5 percent if the state has no approved enhanced mitigation plan. In 2006, the formula became a "sliding scale" for most states: up to 15 percent for the first 2 billion; up to 10 percent for 2-10 billion; up to 7.5 percent for 10-35 billion. For certain states with enhanced ex-ante mitigation planning, the ceiling was up to 20 percent for 0-35 billion.

[10]Individuals and businesses are not eligible to apply for hazard mitigation assistance grants. However, an eligible applicant or sub-applicant may apply for funding on behalf of individuals and businesses.

with the best investment opportunities will invest at the point when it's the best to do so. Therefore, adapted counties will likely be those with different underlying disaster risk distributions and borrowing dynamics compared to an average county, and cross-sectional or time-series estimates of the relationship between the outcome variables and adaptation may be biased. The task of this paper is to develop a valid counterfactual for the outcomes in adapted counties in the absence of adaptation investments. The particular structure of FEMA hazard mitigation programs enables an identification strategy that is essentially a difference-in-differences (DD) research design.

First, funding availability varies across space and over year. Since not all counties invest into adaptation in each year and for each county, adaptation investments happen periodically, I can flexibly control for unobservables that are time-invariant in a county and unobserved common shocks in a period. Therefore, the identification will only come from changes in outcomes within each county and over time.

Figure 1.1a-1.1b maps the panel variation over time. Although there is some concentration in coastal counties, there is a wide geographical dispersion of adaptation investment across the nation. Importantly, for counties that are close in proximity, and therefore likely share similar local risk environment, the timing of investments still varies, suggesting that investments are likely be driven by factors other than exposure to climate risks.

However, making use of changes in outcomes within each county and over time is not enough to guarantee an unbiased estimate. One potential issue is that investment decisions could be correlated with unobserved shocks to determinants of debt financing and real estate market outcomes. For example, counties that adapt in a given year may also be those that just experienced elections and form new governing bodies, which will drive change in fiscal condition and disaster preparedness. Moreover, local demand for property-related adaptation may themselves be driven by a more preferable debt market and prosperity of the real estate sector of a county, creating a reverse causality issue.

These concerns are less likely a problem in the setting of this study for two reasons. First, as mentioned, the grant programs were implemented in a way such that some counties suddenly found themselves in a more preferable situation for investing in adaptation relative to the year prior. In particular, this unexpected change is ensured by the fact that FEMA's funding is largely controlled by the realization of specific disaster incidents, whose timing, range and severity can be viewed as uncontrollable and unpredictable. Second, funding for adaptation investment is determined not only by disaster incidents directly affecting a county's outcomes, but also by disaster incidents affecting other counties within the same state and the priorities outlined in mitigation plans. [11]

[11] One may concern that these priorities are themselves a source of endogeneity. In fact, it would not create an issue if states consistently allocate more money to high-risk locations, which will be captured by the county fixed effects, but it would be a source of bias if states dynamically target those counties that

Finally, there is a unique concern stemming from the fact that the disaster incidents inducing adaptation grants will themselves influence debt financing and real estate market outcomes. If this is the case, then relative to non-adapted counties, adapted counties could still have different post-treatment evolution of the outcome variables even in the absence of FEMA grants and adaptation investments. The advantage of my setting is that it's possible for a county outside the disaster area to receive the grant. Besides, among those counties that are in the disaster area and receive grants, the amount of a single grant is largely unlinked from the actual damage or FEMA assistance at the county level. Therefore, I can separately control for lagged disaster effects and there is a lot of remaining variation in adaptation investments after adding these controls. The setting also allows me to examine the "pure" adaptation effects estimated from adaptation investments in non-disaster areas as a sanity check.

Figure 1.2a-1.2b demonstrates the relationship between disaster damage, proxied by federal assistance, and adaptation grant. As shown in panel A, there is an extremely high correlation between total assistance and hazard mitigation assistance grants for each declared major disaster incident at the state level. However, at the county level, even though there is a slightly positive correlation on average, the data points are much more disperse. In addition, many counties have positive damage but zero grant, whereas some counties have zero damage but positive amount of grants.

Case Study: Hurricane Katrina

Hurricane Katrina illustrates how HMGP grants work in practice. As shown in Figure 1.3a-1.3d, before 2005, there had been property-related adaptation investments induced by past disasters in many counties in the four Gulf States: Alabama, Florida, Louisiana, and Mississippi. Past adaptation grants are correlated with the geographical distribution of pre-existing disaster frequency, a noisy measure of climate risk.

In 2005, these four states declared a disaster status after Hurricane Katrina. Louisiana and Mississippi included all counties in their declared disaster areas, whereas Alabama and Florida only included a subset of counties. Most counties in Louisiana received some grant money for property-related adaptation, but only a small handful of counties in Mississippi got new investments. In fact, a clear cut-off can be seen along the border of Louisiana and Mississippi. This is unlikely justified by the disparity in the underlying distribution of climate risk that largely determine the benefit of adaptation, since there was no obvious pattern of state border in the geographical distribution of pre-existing disaster frequency and the disaster zone of Hurricane Katrina. There were some new adaptation investments in Alabama and Florida as well, and importantly, in counties that were not in the declared

have time-varying higher investment returns, which is another specific example of unobserved shocks that correlated with the outcomes. However, this is unlikely as there is a lot of uncertainty in ex-ante estimates of investment returns, and there are other non-economic factors such as politics affecting grant allocation.

disaster areas. For those counties, grants were induced by damage in other counties within the same state.

From this example, we can clearly see the time-series and cross-section variation in investments. Furthermore, the funding rule of HMGP results in idiosyncratic investment patterns in counties that are close in proximity. Finally, grants can go to counties outside disaster areas.

1.4 Data and Descriptive Statistics

This project uses several datasets on adaptation investments, disaster damage, financing behaviors of local governments and real estate market outcomes, merged at the county level. I describe the sources and structures of these data in this section.

Adaptation investments and federal grants - Project-level administrative data on adaptation are obtained from FEMA. These projects cover a wide range of different types of adaptation activities, and are fully or partially funded by FEMA. For each project, available information includes state and county FIPS codes, fiscal year, total project cost, federal share obligated, project type, status, date approved and closed, benefit-cost ratio, which grant program (HMGP, PDM, FMA) it's under and the associated PDD if it is under HMGP.[12]

I keep only projects with non-missing cost and fiscal year in between 1989 and 2018. I exclude projects that can only be attributed to a state, or those locating outside the 48 continental states.[13] Next, I determine whether a project is property-related based on its project type.[14] I then aggregate project-level data to county-year observations. For simplicity, I count

[12]The fiscal year of a project is determined by the disaster declaration date if it's under HMGP, or by the fiscal year from the project identifier if it's under other programs. A project under HMGP must submit the application within 12 months of the disaster declaration date.

[13]Out of the total cumulative project cost funded by FEMA, which amounts to \$17.85 billion in 2018 dollar, \$2.35 billion went to Alaska, Hawaii, Washington DC, or state governments, while \$15.5 billion went to local governments.

[14]This largely overlaps with the definition of "structural hazard mitigation activities" used by Congressional Research Service (CRS): "Hazard mitigation activities are generally categorized as structural and nonstructural. Structural mitigation activities may include physical changes to a facility or development of standards such as building codes and material specifications. Examples of physical changes to a structure are retrofitting a building to be more resistant to wind-hazards or earthquakes, or elevating a structure to reduce flood damage. Nonstructural activities may include community planning initiatives such as developing land-use zoning plans, disaster mitigation plans, and flood plans. Other nonstructural community activities may include participating in property insurance programs and developing warning systems." (CRS 2009). The project types I categorize as property-related include elevating, relocating and retrofitting public and private structures, shoreline stabilization, vegetation management, infrastructure protective measure, and so on. The project types I leave out include planning, public education, construction of safe rooms, buying equipment like generators, and so on. They are mainly for administrative costs, or aim to reduce damage to human life instead of property.

multiple adaptation projects within a county in a calendar year as a single investment. I separately aggregate property-related and other adaptation projects.

The final sample contains 11,629 property-related adaptation projects, aggregated to 5,672 county-year observations, and 11,650 other adaptation projects, aggregated to 7,059 county-year observations. Although there is a large number of adaptation projects that are not property-related, such as saferoom construction, back-up generator purchase and mitigation planning, they only account for $3.4 billion of total investments, while property-related adaptation has an aggregate investment of $12.1 billion. For investments that are not property-related, I compute the year-by-year cumulative total project cost for each county and include them in the regression as a control. Figure 1.4a plots the trends in aggregate adaptation investment. This figure reveals that total adaptation investment swung greatly over time, largely as a consequence of the periodicity of disaster. Hurricanes are the disaster type that induces most adaptation grants, followed by floods and storms, as shown in Table 1.1. More than two-thirds of investments happened in the South and Northeast.

Putting this in the potential-outcomes framework, counties in the final sample can be divided into three groups: control group, treated group with single treatment and treated group with multiple treatments. Figure 1.5a displays a histogram of the total numbers of years in which property-related adaptation investments occur for each county. Among the 3,129 counties, 1,387 counties have no property-related adaptation investment between 1989 and 2018. 625 counties have only one year in which a new adaptation investment occurs, and 1,117 counties experience more than one year of initiation of new adaptation investments, with the maximal number of years of initiation as 20.

Property damage and disaster assistance - I use data on property damage from the Spatial Hazard Events and Losses Database (SHELDUS)[15], a county-level dataset for hazard loss in the U.S. This database is built on the NCEI Storm Events Database[16] of National Oceanic and Atmospheric Administration (NOAA), which collects event-specific information on 48 event types through multiple sources, including insurance companies, fire departments, public media, county officials and so on. SHELDUS develops its own methodology to estimate, aggregate or assign event-specific property losses to counties. I download the pre-aggregated, county-year property damage of all types of events from SHELDUS.

While SHELDUS is the most comprehensive source of property damage resulting from natural disasters, it may suffer from measurement error considering its secondary nature and data manipulation when associating event-level information to counties. To evaluate robustness of my analysis, I also use FEMA's total assistance as an alternative measure of disaster damage. FEMA has two major assistance programs: Individual Assistance[17] and Public

[15] https://cemhs.asu.edu/sheldus
[16] https://www.ncdc.noaa.gov/stormevents/
[17] https://www.fema.gov/assistance/individual

Assistance[18]. Individual Assistance provides financial and direct services to individuals and households affected by a disaster, including temporary housing and repair or replacement of homes. Public Assistance provides grants to local governments to manage disaster response and recovery, including debris removal and repair, replacement, or restoration of publicly owned facilities.

This damage measure is different from the property damage measure through SHELDUS in several ways. First of all, it's administrative data and thus suffers less from measurement error. However, FEMA assistance is disbursed only after disasters that are sufficiently severed and qualified as PDD, and therefore it misses some smaller events that also lead to disaster damage. Meanwhile, since it captures costs primarily from, but not limited to, property damage, it's only a noisy measure of property damage. Finally, disaggregated data are only available after 2002.[19]

Local Government Finance - For debt and borrowing cost, I make use of the Census of Governments and Annual Survey of State and Local Government Finances. It collects comprehensive financial information on different levels of sub-national governments. All governments are required to report in years ending in 2 and 7, while only a subset of governments is surveyed in other years.[20] In my sample, about one-thirds of counties have a balanced panel between 1989 and 2018.

For interest payment, information is only available for total interest paid on all types of debt. For outstanding debt, information is available separately for short-term and long-term debt, broken down by general purpose and different utility sectors. However, more granular information on maturity is not available. Therefore, I construct a simple measure of average borrowing cost by dividing total interest payment by total outstanding debt. Comparing to other studies using municipal bond yield to measure borrowing cost, this approach has both advantages and disadvantages. One advantage is that this is a more comprehensive measure of borrowing cost, as it's based on total level of debt, including those from sources other than publicly-traded bonds. It also allows for more margins of adjustment for borrowers, including over different maturities and utility sectors. The disadvantage is that the analysis cannot be conditional on detailed bond-level controls such as maturity and credit rating.

Property value and new construction - I use the Zillow Home Value Index (ZHVI) as the primary measure of property value and the House Price Index (HPI) from the Federal Housing Finance Agency as an alternative measure in sensitivity analyses. Both indexes are widely used in real estate research, although each is constructed using different methodology.[21]

[18]https://www.fema.gov/assistance/public

[19]Data on Individual Assistance are available after 2002. Data on Public Assistance are available after 1998.

[20]Each government unit has a different probability of being survey, with the probability determined by a function of expenditures, revenues, and debts. Some large counties are surveyed with probability of 1.

[21]For ZHVI, see https://www.zillow.com/research/zhvi-methodology-2019-deep-26226/ for details. For

ZHVI is available in three different tiers. In the main specifications, I use the median tier, which is a smoothed, seasonally adjusted measure of the typical value for homes within the 35th to 65th percentile range for a given county. For HPI, I use the annual county panel (interpolated and not seasonally adjusted) created by Bogin, Doerner, and Larson (2019).

For new construction, I use data from the Building Permit Survey from the Census Bureau. This annual census collects information directly from local building permit offices on the number and valuation of new housing units, and from local area data, estimates are tabulated for counties. It covers all places issuing building permits for privately-owned residential structures.[22]

Ex-ante measures of risk exposure - I measure exposure to climate risks in three ways. First, I rank counties using the distance of each county centroid to the closest coastline, computed using the dist2Line function in R package geosphere. Second, I rank counties based on the pre-existing declared major disaster frequency, computed using PDD data between 1975 and 1988. Third, I rank counties using the pre-existing property damage, scaled by total assessed valuation of taxable properties in the jurisdiction, data of which is obtained from the 1987 Census of Government.

Other economic data - I include a set of covariates to control for time-varying, county-specific local economic conditions that could determine real estate market outcomes and borrowing of local governments.[23] Data on county-level total income, population, employment, dividend income, earning, proprietor income (by non-farm and farm) are from the Bureau of Economic Analysis. I also obtain information on the numbers of establishments in different industries from the County Business Pattern to control for local industrial composition.

Summary statistics of the main variables are shown for the national sample and by regions in Table 1.2. Within the national sample, the average probability of new adaptation investment is 0.07. Once a new adaptation investment occurs, the average project cost is $2.13 million. However, the distribution of project scales is highly right skewed, as the median is much smaller, at $365,000, than the mean. In fact, distributions of most outcome variables are right skewed to different extents. However, when estimating the regression models, I use the original sample but take the natural logarithm of the outcome variables instead of using a winsorized sample. When interpreting the magnitudes of the coefficients of interest, I also use the simple mean instead of the winsorized mean. This approach is preferred because it preserves the skewed nature of disaster consequences. In the sensitivity analysis, I also show

HPI, see https://www.fhfa.gov/PolicyProgramsResearch/Research/Pages/HPI-Technical-Description.aspx for details.

[22]Over 98 percent of all privately-owned residential buildings constructed are in permit-issuing places, according to the Census Bureau.

[23]In fact, most of these factors are explicitly included in the credit rating process of rating agencies. Of course, it's not an exhaustive list. However, I show in sensitivity analyses that it makes little difference by excluding these county-year level controls.

results on samples winsorized at 99% and 95% percentile of the outcome variable.

There are apparent disparities between the South and Northeast and the West and Midwest subsample. On average, counties in the South and Northeast are slightly more populated. Adaptation projects are larger in the South and Northeast, yet the probability of new adaptation investment is similar across regions. Counties in the South and Northeast are more in debt, and borrow at a higher cost. Average property damage and disaster assistance in these counties are more than double those in the West and Midwest, partially due to higher frequency of major disasters. Property values are lower in the South and Northeast, whereas the value of new construction is similar across regions.

1.5 Empirical Strategy

In this section, I discuss the estimation of effects of new adaptation investments on average borrowing cost, total outstanding debt and other real estate market outcomes of interest.

To begin with, I assume that these outcome variables have the following additive linear functional form:

$$Y_{j,t} = \sum_{\tau=0}^{H} \theta^{\tau} I\{Adapt_{j,t-\tau}\} + \mathbf{X}'_{\mathbf{j,t}}\mathbf{\Gamma} + \lambda_j + \lambda_{r,t} + \epsilon_{j,t} \tag{1.5}$$

where $Y_{j,t}$ is the log of the outcome variable in county j and year t. It is a function of current and past adaptation activities. In other words, each new adaptation investment may have long-term impacts, modifying outcomes over multiple periods. I measure adaptation activities[24] using a series of event indicators $I\{Adapt_{j,t-\tau}\}$ which are equal to one if there is any positive adaptation investment initiated in county j and year $t - \tau$.

$\mathbf{X_{j,t}}$ is a vector of control variables varying at county-year level, including income, population, local industrial composition, and so on. These variables proxy the evolving local economic environments. $\lambda_{r,t}$ is a set of region-year fixed effects that capture common shocks to the outcome variable in a region such as El Niño events that alter the Atlantic hurricane seasons, or nationwide shocks such as aggregate shifts in real interest rates. λ_j is a set of county fixed effects that capture any time-invariant, county-specific unobserved determinants of the outcome variable such as geography. They adjust for any cross-sectional differences in the outcome variables across county, and thus the identification will only come from changes in outcomes within each county and over time.

[24] Here I treat adaptation investments as events to establish a clear connection to the potential-outcomes framework. In the sensitivity analyses, I explore alternative specifications also making use of dollar amount of investments. This will influence the interpretation of the coefficients of interest as well. The coefficients in the main specification measure the "extensive margin" of adaptation effects, and in the alternative specification they measure the "intensive margin" of adaptation effects.

The main coefficients of interest[25] are $\theta^\tau, \tau > 0$, which represent the mean effects of past adaptation investments on contemporaneous outcomes in the adapted counties. θ^0 measures the "announcement effect". It's the coefficients of the year when adaptation grants are open for application.

The identifying assumption for this model to provide an unbiased estimate of the coefficients of interest is that there is no other unobserved factor generating a difference in changes in outcomes among counties with different adaptation status conditional on all other explanatory variables. Formally:

$$E\left[\mathbf{I}\{\mathbf{Adapt_{j,t}}\} \times \epsilon_{j,t} | \mathbf{X_{j,t}}, \lambda_j, \lambda_{r,t}\right] = 0$$

where $\mathbf{I}\{\mathbf{Adapt_{j,t}}\}$ is an H+1 by 1 vector that collects the event indicators of adaptation activities $I\{Adapt_{j,t-\tau}\}, \tau \geq 0$.

Although this identifying assumption cannot be tested directly, several indirect tests can shed light on its defensibility. First, the analysis of trends in the outcome variables prior to and after the year of initiation of adaptation investments will be useful for detecting unobserved factors that covary with both adaptation investments and outcomes[26]. Formally, I produce event study graphs by running the following regression:

$$Y_{j,t} = \sum_{-11}^{21} \theta^\tau I\{Adapt_{j,t-\tau}\} + \mathbf{X'_{j,t}}\mathbf{\Gamma} + \lambda_j + \lambda_{r,t} + \epsilon_{j,t} \tag{1.6}$$

where lags beyond 20 years and leads beyond 10 years are binned.

The event study analysis statistically compares the evolution of the outcome variables in adapted and non-adapted counties around the year in which adaptation investments occurs. If federal grants and adaptation investments respond to unobserved shocks that themselves affect debt financing or the real estate sector, then differential trends in the outcome variables should be seen prior to the investment.

Second, one may worry that adapted counties would have different post-treatment evolution of the outcome variable even in the absence of FEMA grants and adaptation investments.

[25] Note that if there is only one new adaptation investment in county j, and zero adaptation investment in other counties, then the average of $\theta^\tau, \tau \geq 0$ will be equivalent to the DD estimate. If there are positive adaptation investments every year, and the event indicators are replaced by the amount of investment, then this will become a distributed lag model. In the setting of adaptation investment, each county can have multiple new adaptation investments, but not every year, or they can have zero adaptation investment.

[26] One concern discussed in the recent DD literature is that staggered adoption bias could invalidate event study as the test for parallel trend assumption. I also run a specification without including the post periods, and pre-period results remain largely unchanged. According to Borusyak, Jaravel, and Spiess (2021), if the overall model is correct, one should still recover good estimates of the pre-event coefficients without introducing the staggered adoption bias

This is in particular a concern considering that the timing of adaptation grants usually coincides with major disasters. Fortunately, the structure of FEMA grants provides different sources of identifying variation, allowing me to probe the robustness of the estimates under different approaches of controlling disaster effects. More specifically, I control for the lagged effects of major disasters in addition to adaptation investments in the following way:[27]

$$Y_{j,t} = \sum_{\tau=0}^{H} \theta^{\tau} I\{Adapt_{j,t-\tau}\} + \sum_{\tau=0}^{H} \alpha^{\tau} Disaster_{j,t-\tau} + \mathbf{X'_{j,t}\Gamma} + \lambda_j + \lambda_{r,t} + \epsilon_{j,t} \tag{1.7}$$

Ideally, I want to control for both the timing and the severity of disasters at the county level, because the extent to which a county is affected by a disaster could lead to a differential trajectory of the outcome variable. However, it is not feasible in this paper for two reasons. First, I am combining different types of disasters in the study and there is no uniform measure of severity over different disasters such fire and flood. Second, data on county-level disaster assistance, which could be used to proxy disaster damage, were not available until 2002. Therefore, I control for disaster effects in two alternative ways. One is to use a series of event indicators $I\{PDD_{j,t-\tau}\}$ which are equal to one if county j is in the declared disaster areas of at least one PDD in year $t - \tau$. Another approach is to use a richer set of features of PDD including duration of disaster incident, total number of counties and population affected within the same state.

In addition, as an additional test, I estimate the adaptation effects using only variations from counties that were outside major disaster areas but received adaptation grants. Formally, I estimate the following model:

$$\begin{aligned} Y_{j,t} = & \sum_{\tau=0}^{H} \theta^{\tau} I\{Adapt_{j,t-\tau} > 0\} \times I\{PDD_{j,t-\tau} = 0\} \\ & + \sum_{\tau=0}^{H} \alpha^{\tau} I\{Adapt_{j,t-\tau} = 0\} \times I\{PDD_{j,t-\tau} > 0\} \\ & + \sum_{\tau=0}^{H} \delta^{\tau} I\{Adapt_{j,t-\tau} > 0\} \times I\{PDD_{j,t-\tau} > 0\} \\ & + \mathbf{X'_{j,t}\Gamma} + \lambda_j + \lambda_{r,t} + \epsilon_{j,t} \end{aligned} \tag{1.8}$$

In this case, θ^{τ} is estimated from comparing adapted counties and non-adapted counties that were outside declared disaster areas.

[27] α^{τ} can be separately identified due to the fact that some counties received adaptation grants without a disaster and some counties hit by a disaster did not receive adaptation grant. It captures the effect of a past disaster incident, including physical damage, post disaster reconstruction and disaster-induced grants other than adaptation grants.

Finally, to increase power, in the estimation I combine the lag variables into five-year bins, or equivalently, constrain the coefficients of variables within each five-year bin to be the same, rather than estimating the full set of $\theta^\tau, \alpha^\tau, \delta^\tau, \tau > 0$.

1.6 Results and Discussion

Debt Financing of Local Governments

I start by documenting the results on the relationship between adaptation investments, borrowing costs and outstanding debt. Tables 1.3 and 1.4 report estimates of the coefficients of interest θ^τ in equations (5), (7) and (8) using the national sample. Column (1) does not control for disaster effects; column (2) controls for disaster effects using timing of disasters; column (3) controls for disaster effects using a set of PDD features; column (4) uses only variation from counties outside disaster areas. In table 1.3, the natural logarithm of average borrowing cost, or interest paid per $10,000 outstanding debt, is the dependent variable. In table 1.4, the natural logarithm of total outstanding debt is the dependent variable. Indicators that capture the timing of investments are the independent variables.

Results in table 1.3 suggest that there is a consistent reduction in average borrowing cost after adaptation investments. These effects first grow in magnitude and then decrease gradually over time. The estimates are not precise in general, with some exceptions. Standard errors become larger for more distant periods naturally because new adaptation investments roll out over time. Controlling for disaster effects in different ways only changes the estimates slightly, but in general results are robust across specifications.

As shown in column (3) of table 1.3, each additional new adaptation investment decreases the average borrowing cost by 2.2% in the first 5 years, 1.7% in year 6-10, 4.4% in year 11-15 and 2.9% in year 16-20. Given the sample mean of average borrowing cost in the national sample, which is 598 basis points, the absolute level of decrease ranges between 10-26 basis points, and the average 20-year effect is 16 basis points. Effects beyond 20 years seem to converge back to zero.[28]

In contrast, estimates of the effects on outstanding debt are less precise. There is a slight increase in outstanding debt at the beginning, but the effects become negative overtime. As shown in column (3) of table 1.4, the 20-year average change is a 1% increase, but I cannot reject that this estimate is no different from zero.

[28] What may explain that effects fade away after 20 years? One possibility is that there is limited use life of adaptation projects. Another possibility is that the estimates are from a small subset of observations of different nature. Afterall, in early years of the grant program FEMA funded projects of smaller scales, mainly induced by earthquake, and there was substantial increase in total funding after the 1993 and 2000 amendments.

Table 1.5 focuses on the specification that controls for disaster effects using a set of disaster features in equation (7), and reports estimates based on regional subsamples. Results reveal that the national decrease in average borrowing cost due to adaptation investments is largely driven by the South and Northeast. In this subsample, there is significant reduction in the first 20 years, with an average of 25 basis points each year. The estimates from the West and Midwest subsample demonstrate no clear pattern and the hypothesis that these effects are zero cannot be rejected. Similarly, it is the South and Northeast that contribute to the national decrease in outstanding debt. These regions see significant decrease in outstanding debt, amounting to an average of 4.2%, or $4.7 million of debt reduction in the first 20 years. In contrast, there seems to be an immediate increase in outstanding debt in the West and Midwest, although the effects become negative eventually.

Event study analysis presented in figure 1.6a and 1.6b supports the casual interpretation of these results. There is no clear pre-trend in years before the initiation of adaptation investments, suggesting that the evolution of both average borrowing cost and outstanding debt are not statistically different in adapted and non-adapted counties. After the new adaptation investment is put into place, adapted counties start to see gradual decrease in average borrowing cost and outstanding debt relative to non-adapted counties. Changes are in general not immediate due to the time needed for project development. Unfortunately, using single-year indicators sacrifices the power of estimation, so estimates are generally imprecise in the event study.

The Real Estate Sector

The next set of analysis focuses on the impacts of property-related adaptation investments on different outcomes of the real estate market. First, I examine whether the main goal of these investments is achieved. In other words, whether property damage resulting from disasters is reduced. Property damage is measured using data from both SHELDUS and FEMA. Second, I test whether adaptation investments increase average home value within a county. Adaptation could affect home value by capitalization of averted future property damage directly. It could also reflect homeowners' other hedonic valuation of adaptation activities. For example, building a sea wall or cleaning up a forest could change the landscape in local communities. However, it's hard to form a prior about the direction of change. Another caveat is that unlike a conventional hedonic analysis, it's hard to define the spatial range in which adaptation will take effects. In other words, it's hard to translate these adaptation investments into attributes for a specific group of homes. Finally, I examine the effects on new construction, which also to some extent measure market participants' assessment of whether these adaptation projects do protect property effectively. In particular, it captures the view of potential entrants in the market.

Table 1.6 reports results from estimating equation (7) controlling for disaster effects using a set of PDD features and for the national sample. The dependent variables are property damage from SHELDUS in column (1); total assistance from FEMA in column (2); Zillow Home Value Index in column (3); value of new construction in column (4). All dependent variables enter the regressions in natural logarithmic form.

Results imply that there is a contemporaneous increase in damage and total assistance, and a decrease in home value. This is due to the fact that adaptation investments usually occur at the same time as major disasters, and more damaged counties are more likely to invest in adaptation. Property damage is significantly reduced after new investments, with the effects largest in the first 5 years and smaller in subsequent years. Although the two measures of property damage are constructed in very different ways, they lead to results that are of extremely similar patterns. As shown in column (1) of table 1.6, the average reduction in property damage in the first 20 years is 4.5%, or $214,000 of averted damage per year. The average in the first 15 years is even higher, at $323,000 of averted damage per year. A similar pattern is seen in column (2) of table 1.6. The 20-year average reduction is 12%, or $144,000 of averted FEMA assistance for disaster damage annually.

Changes in average value of median-tier homes are small and insignificant. In the sensitivity analyses, I also look at the effects on average home value of cheaper and more expensive homes, and on FHFA's indexes which are constructed differently from Zillow's indices. Results are similar across different measures of home value. In contrast, increases in the value of new construction after the initiation of adaptation investments is significant, grows in magnitude over time and potentially lasts for more than 20 years. The 20-year average increase is 6.7%, or $3.2 million. These findings suggest that the increase in collateral value that potentially explains the reduction in borrowing cost is not due to higher valuation of existing property, but through enlarging the total stock of property in the jurisdiction.

Event study graphs in figure 1.7a-1.7d confirm that these are causal impacts of adaptation investments on real estate market outcomes. Again, no differential trend in the outcomes of interests is detected before the initiation of investments. In the year of initiation of investments, there are jumps in property damage and total assistance. After adaptation investments are in place, property damage and total assistance generally become lower, although there is no clear trend over time. There is a gradual and persistent increase in new construction after the adaptation investments are put in place, whereas no obvious pattern is observed in average home value.

Furthermore, I investigate potential heterogeneity in adaptation effects across region, and whether adaptation is more effective during major disasters. To test these, I estimate the regressions for regional and PDD-year subsamples, with results presented in table 1.7. Indeed, I see that adaptation investments reduce property damage more during major disasters and in the South and Northeast.

Costs, Benefits and Returns of Property-Related Adaptation Investments

To facilitate the comparison of benefits of adaptation investments across regions, and to compare them with returns on broader types of investment in practice, I calculate the implied 15-year internal rate of return (IRR) using outputs from the empirical analysis. In particular, I use the sample mean of cost of adaptation and assume all costs are paid in the year of initiation. I then compute the annual averted property damage in the first 15 years using the estimates from column (1) of table 1.6 and column (3) of table 1.7 for the national sample and South and Northeast subsample, respectively. I assume conservatively that the project only pays off for 15 years.

Table 1.8 presents the results. Based on the average project cost and property damage, the implied 15-year IRR in the national sample is 19%. The implied 15-year IRRs for the South and Northeast subsample is even higher, mainly driven by larger estimated percentage reduction in property damage as well as larger sample mean of property damage.

These results suggest that there is a strong return on investment for adaptation, and there may be too little investment currently. Considering the average borrowing cost of 5.98% in the national sample, the opportunity cost of capital needed for financing adaptation investment revealed by the municipal debt market seems much smaller than the implied IRRs. Therefore, it's socially beneficial for an average local government to borrow from the municipal debt market to finance more adaptation investments instead of waiting for FEMA's grants. Moreover, while the implied IRRs are considerably higher in the South and Northeast, the sample means of average borrowing cost are similar in the two regional subsamples, as shown in table 1.2. This suggests that given current spending, the total benefit from adaptation investment can be increased by redistributing more money to the South and Northeast.

There are several caveats that the readers should keep in mind when interpreting these IRRs. One is that I only observe the development costs of adaptation investment and ignore the subsequent operating and maintenance costs. This may or may not be a satisfying approach. For certain adaptation activities, such as elevating or retrofitting a structure, it's safe to assume that costs are one-time. But for other activities such as vegetation management or shoreline stabilization, continual maintenance is needed, so costs observed in the data may underestimate the total cost of adaptation. While I don't have data on operating costs, it's useful to gauge the magnitude of these costs through a back-of-the-envelope calculation. With the development cost and annual averted property damage fixed at the current level, to bring the 20-year IRR down from 19% to 6%, the annual implied operating cost would be more than half of the annual averted property damage. The sum of 15-year operating cost would be more than double of the development cost. Thus, it's unlikely that missing operating cost can rationalize the sizable IRRs.

Meanwhile, I also only observe a subset of all possible benefits from these adaptation investments. At the same time as they reduce property damage, they could also benefit the homeowners in other ways such as protecting human life and other personal property including motor vehicles. With increased frequency and intensity of natural disaster in the future due to climate change, adaptation benefits will likely become even larger.

Another caveat is that I only observe how these adaptation projects recoup the investments ex-post. If there has been a systematic underestimation of adaptation benefit ex-ante, investments would be at efficient level from an ex-ante view.

Moreover, adaptation projects examined in this study are of very different scales and different in nature. Therefore, it may not be appropriate to apply the estimates based on the average to an adaptation project of a specific type or scale.

Finally, the implied IRR is a social rate of return rather than a measure of profitability of adaptation investments. Without an appropriate business model and a stable revenue stream, adaptation investments may not be recouped by a specific entity.

What may explain the under-investment in property-related adaptation, i.e., the "adaptation gap"? According to Fankhauser (2017), a long list of political, market, and behavioral factors including coordination problems and shortsightedness of government agencies, incomplete pricing of climate risks in financial markets, moral hazard related to disaster assistance and insurance, inertia and present bias of homeowners can lead to inadequate adaptation. Furthermore, uncertainty in adaptation benefit could also undermine the incentive in investment. While this does not seem to be the concern based on the findings about averted property damage in this study, it could matter in ex-ante cost-benefit analysis. Lastly, even though there is large discrepancy between average rate of return of adaptation and average borrowing cost, local governments may not be able to exploit potential investment opportunities due to several reasons: the statutory or constitutional debt limit that prevent further borrowing; concern about conveying negative message to creditors; lack of good business model to create a stable revenue stream for structuring a revenue bond. Although it is not the focus of this paper, it could be valuable for future research to explore the underlying mechanisms that lead to under-investment empirically.

How about spatial misallocation in capital resources? It is likely a result of a funding rule that arbitrarily links adaptation grants to damage from particular disaster incidents rather than returns of individual projects. Indeed, there have been proposals and efforts to reform the system of Hazard Mitigation Assistant Grant to shift resources from post-disaster and pre-disaster mitigation and give more weight to cost effectiveness in project selection (GAO 2021).

Sensitivity Analyses

I probe the robustness of the estimates to several adjustments of the regression model. Results are included in the appendix. In general, I find little evidence contradicting the basic conclusions of this paper.

More specifically, I repeat the regression with no control for local economic condition, alternative time fixed effects and state-specific linear time trends. I also investigate alternative ways to measure outcomes. In particular, I run specifications with outcome variables in level instead of in natural logarithm, and scale outcomes by population. I try different ways of constructing the treatment variable as well. Specifically, I define the year of the very first adaptation investment as the treatment variable, which will become a conventional DD with variations in timing of treatment for each unit. I also further combine the event indicators and only study the effects of cumulative adaptation investments. Moreover, I examine the intensive margin of adaptation investment. In the baseline model, large and small adaptation projects are treated in the same way, but we may want to see whether increasing the scale of a single adaptation project will have additional effects. Finally, I look at other dimensions of treatment effect heterogeneity, including over time and across different bins of climate risk exposure. I also break down the treatment effect by different types of initiating disaster incidents.

1.7 Conclusion

This paper empirically investigates the relationship between adaptation investments, property damage and debt financing of local governments. The prosperity of the real estate sector in a locality has important impacts on borrowing costs of the local government for funding public service and infrastructure development, including adaptation to changes in environment. Climate change leads to higher risks of physical damage to real property, making it not only more costly to manage disaster recovery, but also more difficult to secure revenue from property taxes and to finance investments to reduce future damage. Adaptation can reduce the risk, which benefits a locality by both directly reducing damages and indirectly lowering borrowing costs.

I leverage variation from a large federal program that funds adaptation investments for local governments to study the effects of property-related adaptation on the local real estate market, direct property damages, and borrowing costs. I find that new property-related adaptation investments decrease average borrowing cost by 10-26 basis points for 20 years. Property damage declines substantially, especially in early years. While there is negligible change in home values, a gradual and persistent increase in new construction is found. The implied 20-year IRR of an average adaptation project is 18% nationally, and it is even higher in the South and Northeast.

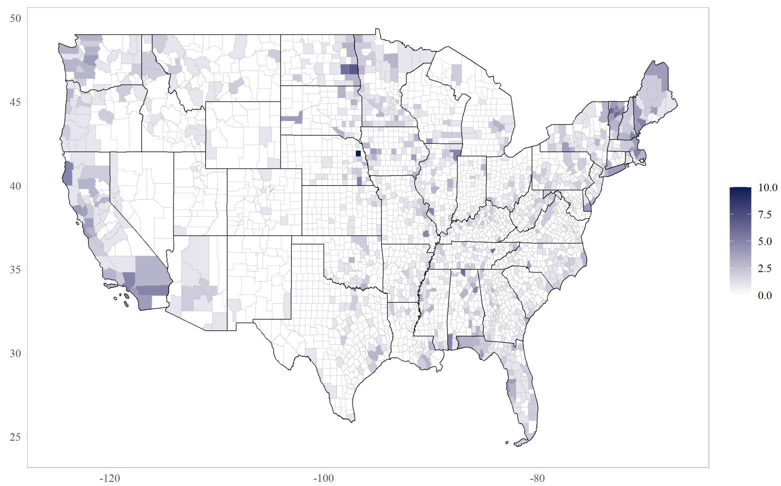
This sizable IRR is mainly driven by large short-term decreases in property damage. This seems counter to the view that payoffs to adaptation are uncertain given the unpredictable nature of disasters, and that investment costs can only be recouped in the long term. The observed pattern emphasizes the need for careful examination of how adaptation projects work in reality and who actually capture the benefits using more granular data. These types of studies will improve future planning for adaptation investments.

In light of recent debates on how the financial system should prepare for climate change, the results of this paper suggest that adaptation can play a key role in risk management. However, there is a dilemma in terms of how to finance adaptation investments. A free-market solution is only optimal if the benefit is fully appreciated by the beneficiary, yet this is usually not the case in practice. The current system of financing these investments through public funds allocated by the federal government could address the concern of lack of incentives, but it may generate another form of inefficiency by misallocating funds away from places that benefit most from them. To improve the efficiency in adaptation investments, policy reforms may be considered to address specific sources of under-investment and adopt alternative funding rules that have a forward looking focus rather than being largely reactive in the way that the grant program is currently structured.

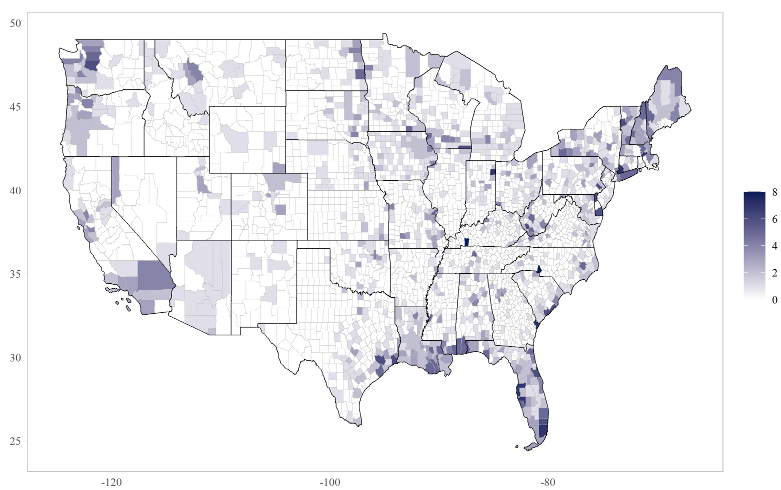
Figures and Tables

Figure 1.1: Geographic Distribution of Property-Related Adaptation Investments over Time

(a) 1989-2003



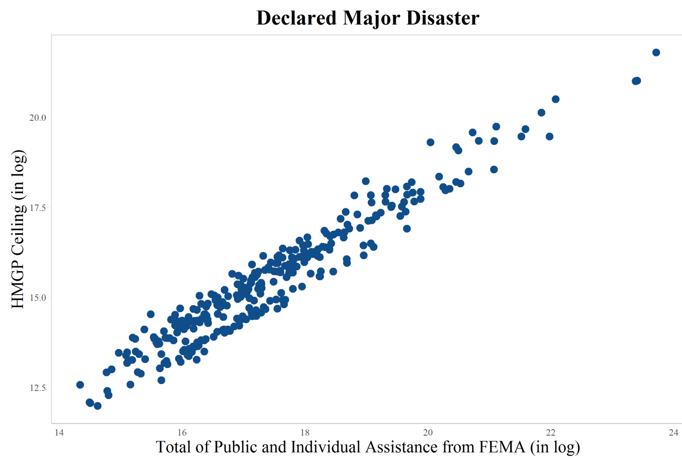
(b) 2004-2018



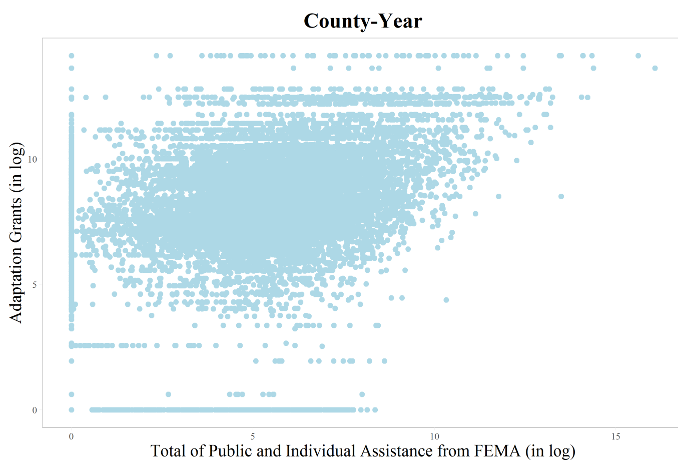
Notes: These maps show numbers of years in which property-related adaptation investments occur by county between 1989 and 2003, and 2004 and 2018. Counties in white are those without property-related adaptation investment.

Figure 1.2: Amount of Adaptation Grant is Closely Linked to Disaster at the State Level, but Largely Unlinked from Disaster at the County Level

(a) Disaster Damage and HMGP Ceiling, by State-Level Declared Major Disaster

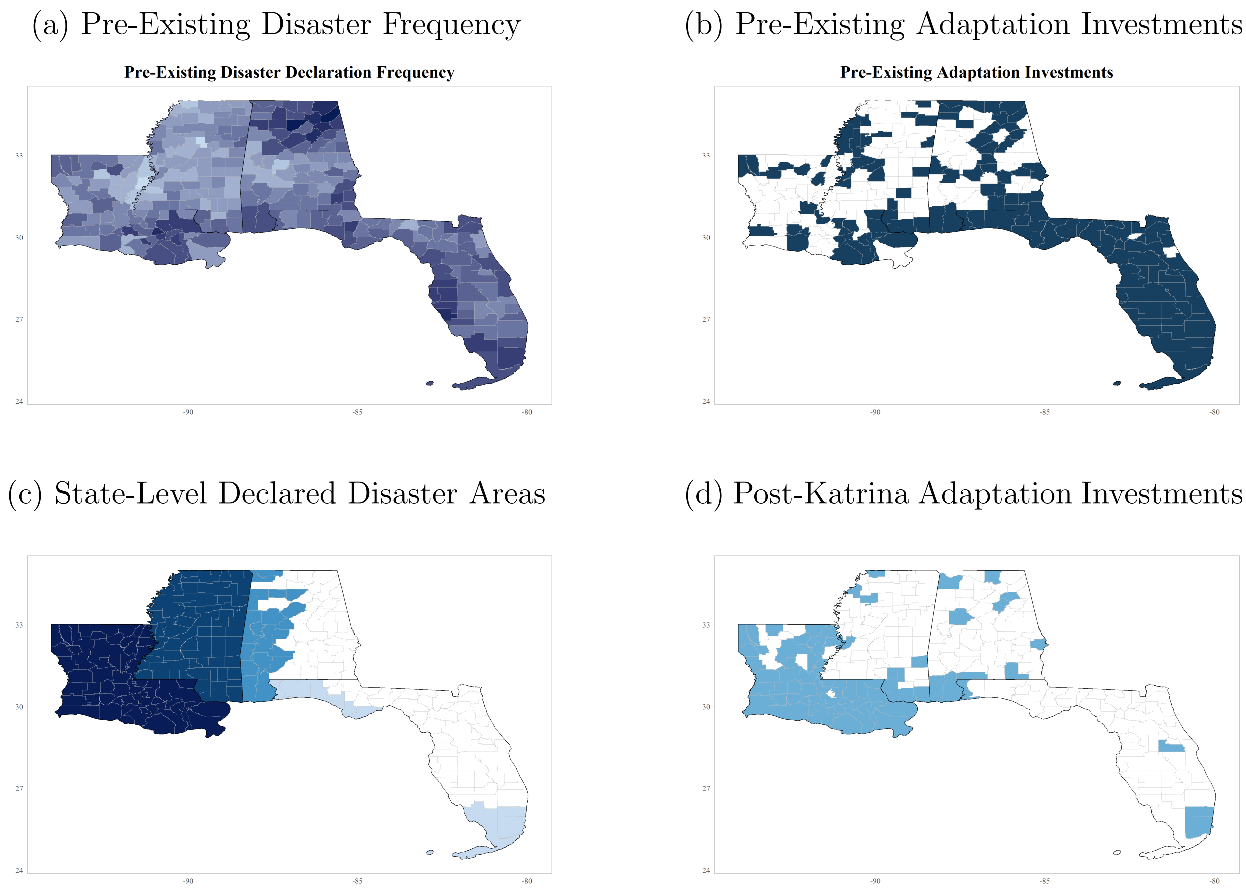


(b) Disaster Damage and Adaptation Grants, by County and Year



Notes: These scatter plots show the correlation between total assistance (public assistance + individual assistance) and grants for all adaptation investments from FEMA between 2002 and 2018. In panel (a), each dot represents a unique state-level declared major disaster. FEMA will determine the funding for adaptation activities by a lock-in, which acts as a ceiling for funds available to state and local governments for a given state-level declared major disaster. It's based on a percentage of the estimated total assistance under the Stafford Act. In panel (b), each dot represents a county-year. Federal grant is calculated as the sum of amount of FEMA grants for adaptation activities received by a county in one year. County-year observations with zero total assistance and/or zero federal grant are included the sample with plus one adjustment.

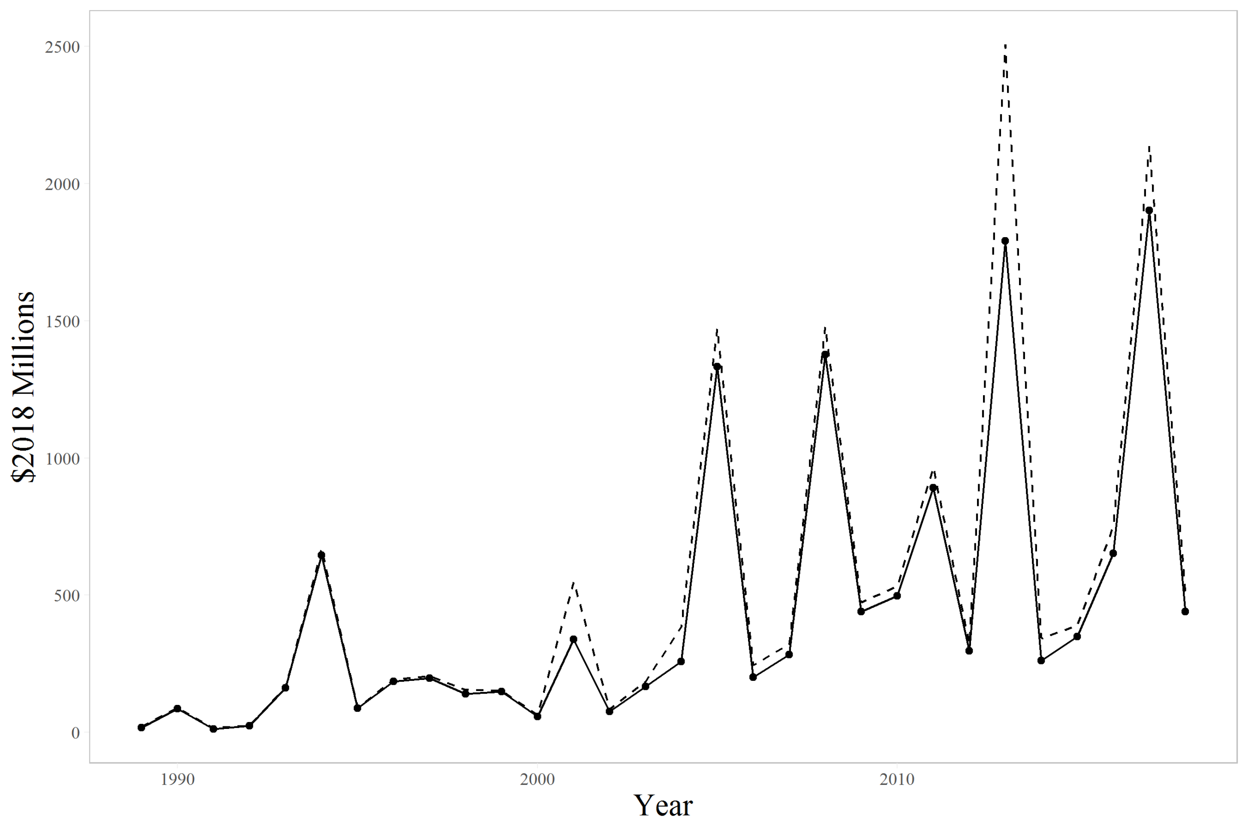
Figure 1.3: Hurricane Katrina as an Illustration of Policy Variations



Notes: These figures show the geographical distribution of pre-existing frequency of declared major disaster, or Presidential Disaster Declaration (PDD), pre-existing property-related adaptation investments, counties included in state-level declared disaster ares for Hurricane Katrina, and post-Katrina adaptation investments. Counties in the four affected states, Louisiana, Mississippi, Alabama, and Florida, are shown. Pre-exisiting frequency of declared major disaster is calculated based on data between 1989 and 2004. Counties in white are those without property-related adaptation investment or outside declared disaster areas.

Figure 1.4: Total Adaptation Investment, 1989-2018

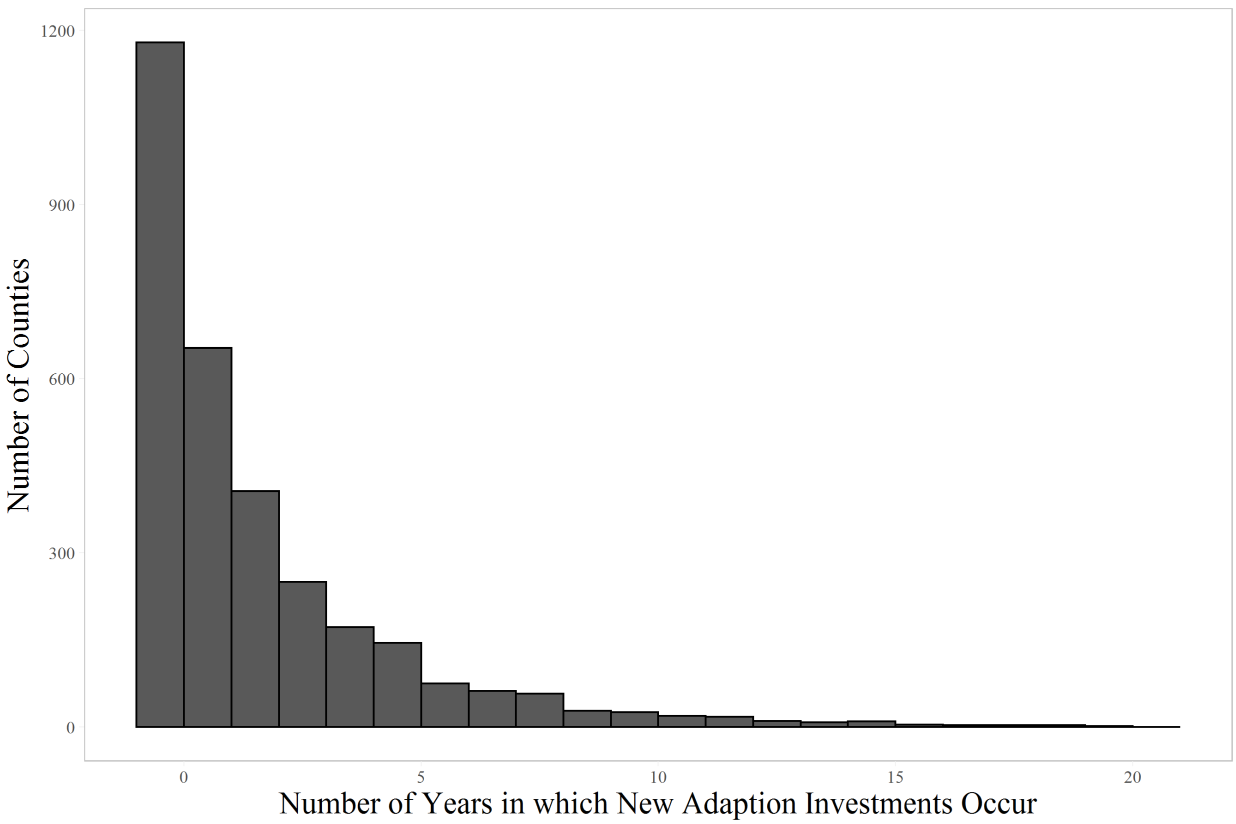
(a)



Notes: This figure shows annual total cost of all (dashed line) and property-related only (solid line) adaptation projects funded partially and fully by FEMA between 1989 and 2018. Projects that cannot be linked to a specific county in the continental United States are excluded from the calculation.

Figure 1.5: Distribution of Cumulative Numbers of Years in which New Adaptation Investments Occur

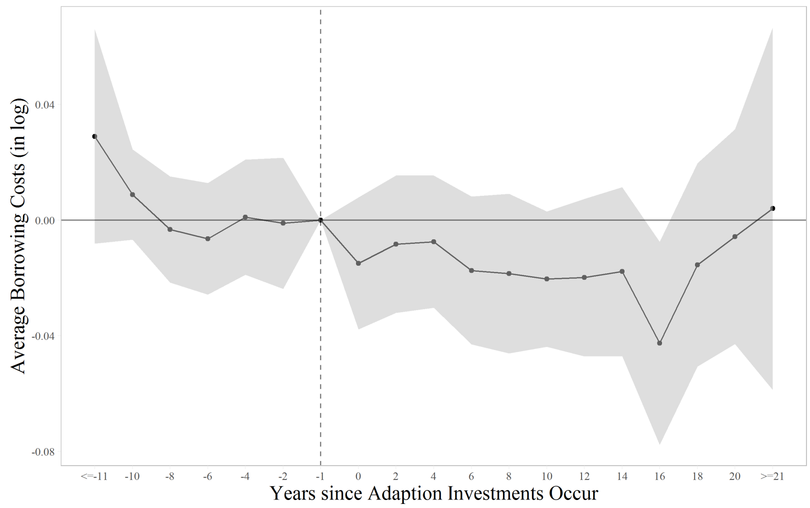
(a)



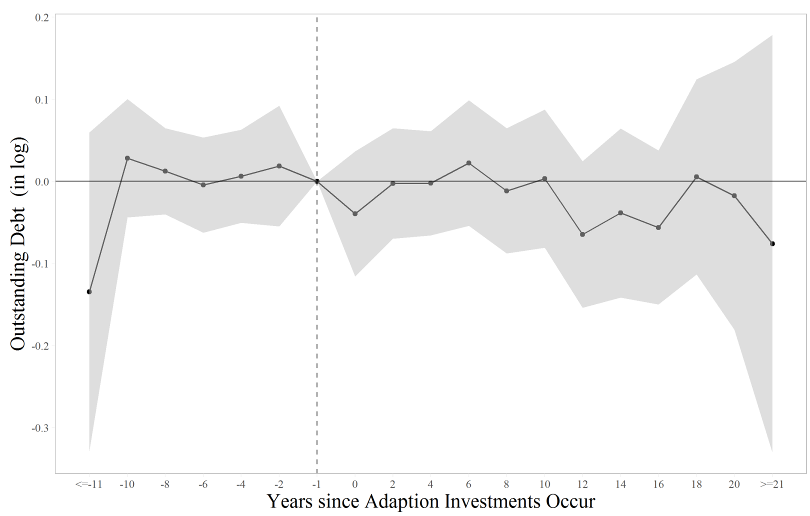
Notes: The figure shows the distribution of total numbers of years in which property-related adaptation investments occur. Each observation is a county, and there are 3129 unique counties in the sample. 1387 counties have no property-related adaptation investment between 1989 and 2018. 625 counties have only one year in which a new adaptation investment occurs, and 1117 counties experience more than one year of initiation of new adaptation investments, with a maximum of years of initiation as 20.

Figure 1.6: Effects of Adaptation Investments on Debt Financing: Event Study Graphs

(a) Average Borrowing Cost



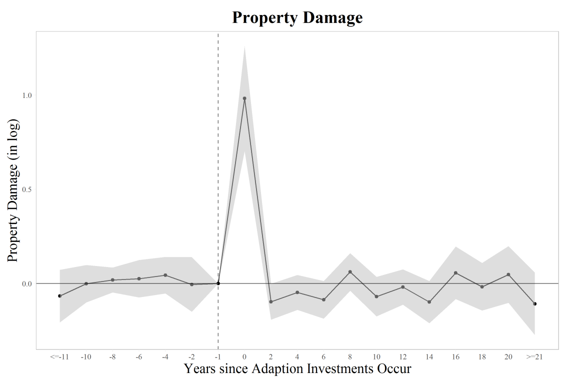
(b) Outstanding Debt



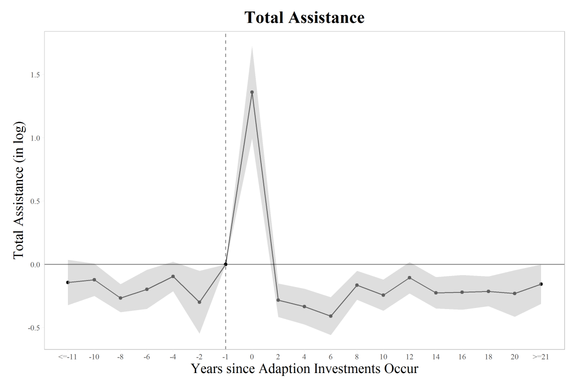
Notes: These figures plot the dynamics of changes in average borrowing cost and outstanding debt before and after the year in which adaptation investments occur. The coefficient for the year before the investment event is normalized to zero. Solid points show point estimates and vertical segments show 95% confidence intervals.

Figure 1.7: Effects of Adaptation Investments on the Real Estate Sector: Event Study Graphs

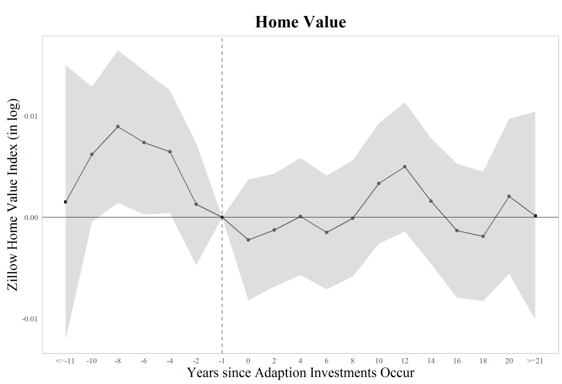
(a) Property Damage



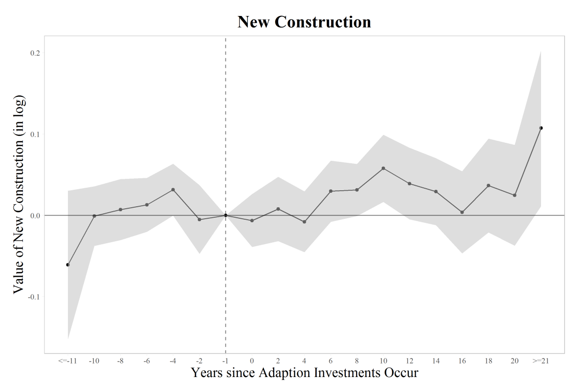
(b) Total Assistance



(c) Home Value



(d) New Construction



Notes: These figures plot the dynamics of changes in property damage, total assistance from FEMA (an alternative measure of disaster damage), home value and new construction before and after the year in which adaptation investments occur. The coefficient for the year before the investment event is normalized to zero. Solid points show point estimates and vertical segments show 95% confidence intervals.

Table 1.1: Descriptive Statistics of Property-Related Adaptation Investments

	(\$2018 Million)
Total project cost	\$12,123
(Federal share)	\$9,294
By project type	
For building (e.g. acquisition, elevation, floodproofing, retrofitting, relocation)	\$6,884
For surrounding environment (e.g. infrastructure, land stabilization, vegetation)	\$5,239
By region	
South and Northeast	\$8,698
West and Midwest	\$3,425
By initiating disaster type (top 5 only)	
Hurricane	\$5,394
Flood	\$2,365
Storm	\$2,306
Earthquake	\$628
Fire	\$280

Notes: Total project cost is calculated as the sum of costs of property-related adaptation projects funded partially and fully by FEMA between 1989 and 2018. Projects that are not property-related and cannot be linked to a specific county in the continental United States are excluded from the calculation. Federal share is calculated as the sum of federal obligations to projects included in the sample. Project type is based on FEMA's categorization of project type and the author further combines the original categories into broader categories. Initiating disaster type is based on FEMA's categorization of PDD or sub-programs that induce adaptation funding, and the author further combines the original categories into broader categories.

Table 1.2: Summary Statistics

	National	South and Northeast	West and Midwest
Project cost ($000)	**2,136** — 365	**2,616** — 361	**1,457** — 371
	(15,029)	(18,315)	(8,383)
Year of initiation of adaptation investment (=1)	**0.07** — 0	**0.07** — 0	**0.05** — 0
	(0.25)	(0.25)	(0.22)
Average borrowing cost (basis point)	**598** — 523	**610** — 543	**584** — 502
	(493)	(474)	(515)
Outstanding debt ($000)	**86,645** — 5,531	**113,264** — 10,977	**59,291** — 2,486
	(439,481)	(515,577)	(342,042)
(Long-term only)	**84,974** — 5,428	**111,129** — 10,796	**58,098** — 2,445
	(431,265)	(505,813)	(335,837)
Property damage ($000)	**4,751** — 30	**6,664** — 38	**2,587** — 23
	(149,144)	(187,652)	(86,955)
Being affected by declared disasters (=1)	**0.31** — 0	**0.35** — 0	**0.26** — 0
	(0.46)	(0.48)	(0.44)
Total disaster assistance ($000)	**1,199** — 0	**1,978** — 0	**317** — 0
	(52,782)	(72,277)	(5,108)
Home value ($000 per home)	**118** — 97	**109** — 89	**130** — 107
	(83)	(77)	(89)
New construction ($000)	**46,477** — 4,756	**48,595** — 5,535	**44,147** — 4,133
	(52,782)	(167,439)	(193,316)
Total population (persons)	**92,838** — 25,414	**97,291** — 30,983	**87,801** — 20,060
	(300,051)	(231,167)	(362,475)
Number of distinct counties	3,129	1,661	1,468

Notes: **Means** — medians and standard deviations (in parentheses) are presented.

Table 1.3: Effects of Adaptation Investments on Average Borrowing Cost

	Average borrowing cost (in log)			
	No disaster control	Disaster timing	Disaster features	Non-Disaster areas
	(1)	(2)	(3)	(4)
New adaptation investments occurred in:				
last 1–5 years	-0.025*	-0.023	-0.022*	0.005
	(0.014)	(0.014)	(0.013)	(0.017)
last 6–10 years	-0.025	-0.023	-0.017	-0.010
	(0.019)	(0.019)	(0.016)	(0.017)
last 11–15 years	-0.057***	-0.059***	-0.044***	-0.031
	(0.020)	(0.020)	(0.016)	(0.024)
last 16–20 years	-0.030	-0.036	-0.029	-0.022
	(0.027)	(0.027)	(0.024)	(0.029)
last 21 or above years	-0.001	-0.003	-0.007	0.034
	(0.033)	(0.034)	(0.033)	(0.033)
Local economic condition controls	X	X	X	X
Lagged disaster timing controls		X		
Lagged disaster feature controls			X	
Adaptation in non-disaster areas				X
County FE	X	X	X	X
RegionXYear FE	X	X	X	X
Observations	47,974	47,974	47,974	47,974

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. Average borrowing cost is calculated by dividing total interest payment by total outstanding debt (including short- and long-term debt), and enters a regression in natural logarithmic form. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Local economic condition controls include total income, population, dividend payment, all earnings, proprietor income (non-farm and farm), and number of establishments in different sectors. Lagged disaster timing controls include a set of disaster indicators, constructed in a way similar to adaptation investment events. Lagged disaster feature controls include duration in number of days, total population and total number of counties affected in a state. These variables are constructed using PDD-level information and binned in a way similar to adaptation investment events. If the county falls into declared disaster areas for more than one PDD in a year, duration, population and number of counties affected are summed. Adaptation in non-disaster areas are estimated by comparing adapted and non-adapted counties outside declared disaster areas. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01

Table 1.4: Effects of Adaptation Investments on Outstanding Debt

	Total outstanding debt (in log)			
	No disaster control	Disaster timing	Disaster features	Non-Disaster areas
	(1)	(2)	(3)	(4)
New adaptation investments occurred in:				
last 1–5 years	0.081	0.082	0.075	-0.027
	(0.052)	(0.052)	(0.048)	(0.050)
last 6–10 years	0.019	0.018	0.042	-0.038
	(0.067)	(0.068)	(0.066)	(0.066)
last 11–15 years	-0.060	-0.061	-0.043	-0.021
	(0.068)	(0.069)	(0.066)	(0.069)
last 16–20 years	0.025	0.019	-0.031	-0.073
	(0.085)	(0.081)	(0.082)	(0.121)
last 21 or above years	0.005	0.023	-0.054	0.197
	(0.133)	(0.133)	(0.127)	(0.145)
Local economic condition controls	X	X	X	X
Lagged disaster timing controls		X		
Lagged disaster feature controls			X	
Adaptation in non-disaster areas				X
County FE	X	X	X	X
RegionXYear FE	X	X	X	X
Observations	60,284	60,284	60,284	60,284

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. Total outstanding debt is the sum of short- and long-term outstanding debt, and enters a regression in natural logarithmic form (with plus one adjustment). Thus, county-year with zero level of debt (about 20% of the national sample) enter a regression as zero. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Local economic condition controls include total income, population, dividend payment, all earnings, proprietor income (non-farm and farm), and number of establishments in different sectors. Lagged disaster timing controls include a set of disaster indicators, constructed in a way similar to adaptation investment events. Lagged disaster feature controls include duration in number of days, total population and total number of counties affected in a state. These variables are constructed using PDD-level information and binned in a way similar to adaptation investment events. If the county falls into declared disaster areas for more than one PDD in a year, duration, population and number of counties affected are summed. Adaptation in non-disaster areas are estimated by comparing adapted and non-adapted counties outside declared disaster areas. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 1.5: Effects of Adaptation Investments on Debt Financing, by Region

	Average borrowing cost (in log)		Total outstanding debt (in log)	
	South and Northeast	West and Midwest	South and Northeast	West and Midwest
	(1)	(2)	(3)	(4)
New adaptation investments occurred in:				
last 1–5 years	-0.027*	-0.007	-0.024	0.213**
	(0.015)	(0.023)	(0.046)	(0.076)
last 6-10 years	-0.043*	0.020	-0.100	0.239**
	(0.023)	(0.017)	(0.070)	(0.102)
last 11–15 years	-0.046***	-0.026	-0.114	0.097
	(0.016)	(0.028)	(0.069)	(0.106)
last 16–20 years	-0.049	0.006	0.070	-0.063
	(0.034)	(0.030)	(0.079)	(0.143)
last 21 or above years	-0.007	0.017	-0.047	-0.022
	(0.042)	(0.045)	(0.138)	(0.239)
Local economic condition controls	X	X	X	X
Lagged disaster feature controls	X	X	X	X
County FE	X	X	X	X
RegionXYear FE	X	X	X	X
Observations	26,305	21,669	30,552	29,732

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. Average borrowing cost is calculated by dividing total interest payment by total outstanding debt (including short- and long-term debt), and enters a regression in natural logarithmic form. Total outstanding debt is the sum of short- and long-term outstanding debt, and enters a regression in natural logarithmic form (with plus one adjustment). Thus, county-year with zero level of debt (about 20% of the national sample) enter a regression as zero. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Local economic condition controls include total income, population, dividend payment, all earnings, proprietor income (non-farm and farm), and number of establishments in different sectors. Lagged disaster feature controls include duration in number of days, total population and total number of counties affected in a state. These variables are constructed using PDD-level information and binned in a way similar to adaptation investment events. If the county falls into declared disaster areas for more than one PDD in a year, duration, population and number of counties affected are summed. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 1.6: Effects of Adaptation Investments on the Real Estate Sector

	Property damage (1)	Total assistance (2)	Zillow Home Value Index (3)	New construction (4)
New adaptation investments occurred in:				
last 1–5 years	-0.123**	-0.214***	-0.001	0.042
	(0.049)	(0.044)	(0.004)	(0.033)
last 6–10 years	-0.062	-0.121**	0.0005	0.095***
	(0.054)	(0.053)	(0.005)	(0.029)
last 11–15 years	-0.018	-0.019	0.003	0.083**
	(0.054)	(0.058)	(0.005)	(0.037)
last 16–20 years	0.024	-0.126*	-0.003	0.059
	(0.070)	(0.068)	(0.005)	(0.058)
last 21 or above years	-0.137	0.014	-0.001	0.133**
	(0.086)	(0.082)	(0.006)	(0.054)
Local economic condition controls	X	X	X	X
Lagged disaster feature controls	X	X	X	X
County FE	X	X	X	X
RegionXYear FE	X	X	X	X
Observations	93,870	53,192	46,095	86,720

Notes: Each observation in a regression is a county-year. Property damage is SHELDUS' estimated property loss from natural hazards such thunderstorms, hurricanes, floods, wildfires, and tornados as well as perils such as flash floods, heavy rainfall, and so on. Data cover 1989-2018. Total disaster assistance is the sum of individual and public assistances of FEMA. Data cover 2002-2018. Zillow Home Value Index (median-tier) is a smoothed, seasonally adjusted measure of the typical value for homes within the 35th to 65th percentile range for a given county. Data cover 1995-2018. Value of new construction is the sum of value of new construction of all types of building in Building Permit Survey. Data cover 1990-2018. All outcome variables enter regressions in natural logarithmic form (with plus one adjustment, except for ZHVI). The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Local economic condition controls include total income, population, dividend payment, all earnings, proprietor income (non-farm and farm), and number of establishments in different sectors. Lagged disaster feature controls include duration in number of days, total population and total number of counties affected in a state. These variables are constructed using PDD-level information and binned in a way similar to adaptation investment events. If the county falls into declared disaster areas for more than one PDD in a year, duration, population and number of counties affected are summed. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 1.7: Effects of Adaptation Investments on Property Damage, by Major Disaster Years and by Region

	Property damage (in log)			
	Major disaster years	Years without a major disaster	South and Northeast	West and Midwest
	(1)	(2)	(3)	(4)
New adaptation investments occurred in:				
last 1–5 years	-0.124	-0.029	-0.199***	0.004
	(0.078)	(0.046)	(0.059)	(0.060)
last 6-10 years	-0.092	-0.022	-0.071	-0.021
	(0.110)	(0.051)	(0.075)	(0.067)
last 11–15 years	-0.093	0.046	-0.036	0.032
	(0.103)	(0.061)	(0.083)	(0.075)
last 16–20 years	0.092	0.085	-0.030	0.082
	(0.090)	(0.069)	(0.090)	(0.118)
last 21 or above years	0.059	-0.146	-0.035	-0.185
	(0.136)	(0.088)	(0.119)	(0.133)
Local economic condition controls	X	X	X	X
Lagged disaster feature controls	X	X	X	X
County FE	X	X	X	X
RegionXYear FE	X	X	X	X
Observations	28,745	65,125	49,830	44,040

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. Property damage is SHELDUS' estimated property loss from natural hazards such thunderstorms, hurricanes, floods, wildfires, and tornados as well as perils such as flash floods, heavy rainfall, and so on, and enters a regression in natural logarithmic form (with plus one adjustment). Thus, county-year with zero level of property damage (about 22% of the national sample) enter a regression as zero. The indicator of "year of initiation of adaptation investment" is based on the fiscal year of the adaptation project documented by FEMA. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table 1.8: Implied Return of Adaptation Investments

	National	South and Northeast
Average project cost	2136	2616
Annual averted property damage:		
In 1-5 years	585	1328
In 6-10 years	296	476
In 11-15 years	87	240
15-year average	323	681
	[-77, 723]	[-79, 1442]
Implied IRR	19%	45%

Notes: All monetary values are deflated to $2018 thousand. Average project cost is the mean of project cost among years in which positive adaptation investments occur and calculated separately for the national sample and South and Northeast subsample. Average annual averted property damage is calculated by multiplying the respective sample mean of property damage by coefficient estimates in Table 6 and 7. Brackets show 95% confidence intervals, calculated using delta method.

Chapter 2

Textual Analysis of Opinions on Climate Change Actions Using Tweets

2.1 Introduction

While the threats of climate change are more and more acknowledged as reality, there is less agreement on how to deal with it. According to the Intergovernmental Panel on Climate Change (IPCC), actions addressing climate change challenges fall into one of the two categories. Mitigation, or reducing carbon emission to slow down the process of climate change, usually through regulations or voluntary programs, is one possible action. Adaptation, or modifying behaviors or the physical environment to lessen exposure to or damage from climate change, such as building sea walls or elevating houses, is another possible action. These two types of actions differ in not only the nature of human response to climate change, but also the decision making process and types of stakeholders involved. While mitigation such as emission regulation is influenced broadly by voter sentiments and the political economy, adaptation is more decentralized in nature. It relies mostly on individual or local government investments, and provides exclusive benefits similar to private good or local public goods such roads or parks. In both cases, individuals' attitudes have great impacts on determining whether and how much to mitigate or adapt.

The goal of this research is to leverage text data to learn about public opinions on climate change and related actions, in particular, mitigation verses adaptation. For a given piece of text, it is possible to for the researcher read through it and determine (a) whether the agent thinks that climate change is a real issue to be addressed; (b) whether actions should be taken; (c) what kind of action the agent tends to take. With labeled data, machine learning models can be trained and applied to extend the classification to large-scale text data with broader spatial and temporal coverage. Resulting predictions can be combined with other datasets for further studies about the causes and consequences of variation in climate opinions. There are many potential sources of text, including tweets, SEC filing of publicly listed firms, newspapers, and so on.

As a first step, I use a small sample of tweets to train machine learning models and evaluate their performances. I begin with tweet data because they directly reflect the speaker's opinions. Moreover, they are succinct, yet can convey rich information that structured data cannot. The advantage of these data compared to survey data is that they provide more degrees of freedom in terms of what type of information to extract. Another advantage is that there could be more granular information about where and when the opinion is expressed. Results of the experiments indicate that a deep learning approach based on contextual embeddings (BERT) outperforms traditional models, and addressing unbalanced classes through up-sampling achieves additional gains in accuracy.

In future analysis, I will apply the trained model on a larger sample, explore variation in predicted labels over time and across locality, and expand the analysis to multiple types of text that likely represent different stakeholders' attitudes. Furthermore, it is possible to link the outputs of the model to data on actual mitigation and adaptation activities and examine how much perception shapes action (and vice versa).

2.2 Related Work

This research is related to several strands of literature. The first strand of directly relevant literature is on media coverage, communication and public opinions about climate change. Barkemeyer et al. (2016) used established metrics to quantify the sentiment and readability of different versions of the IPCC report and compared it to the associated media coverage. Boussalis and Coan (2016) compiled a corpus from think tank publications and used Latent Dirichlet Allocation (LDA) to identify main topics of climate skepticism. Engle et al. (2020) extracted innovations from climate news series constructed through textual analysis of newspapers and built hypothetical portfolios to hedge these innovations. My contribution to this literature is to surpass simple sentiment analysis, measurement of attention or surprise regarding general climate change. Instead, I go deeper to distinguish among opinions on different types of climate actions.

This study is also related to the long-existing literature on adaptation to climate change (see also literature review in the previous chapter). The research goals of most previous papers are to empirically estimate the effects and returns of adaptation efforts, through either investigating specific adaptation technology or treating the heterogeneity in consequences of climate shocks as adaptation. One exceptional paper is Moore et al. (2019), where the authors link the resulting data of sentiment analysis on tweets to weather data and examine "adaptation" in the sense of change in perception about temperature shocks. I depart from previous studies by examining adaptation following the definition used by IPCC, i.e., any effort of modifying behaviors or environment to reduce the impact of climate change. I also focus on opinions rather than the actual action, and simultaneously considering mitigation in a comparable way.

More broadly, in the field of economics and finance, there have been many applications of textual analysis for generating different measures of interest (see Gentzkow, Kelly, and Taddy (2019) and Loughran and McDonald (2020) for a comprehensive review). In an early study, Tetlock (2007) used Wall Street Journal's "Abreast of the Market" column to construct a sentiment index, which was used to predict returns on the Dow Jones Industrial Average. Bollen, Mao, and Zeng (2011) achieved similar goals using twitter messages. Both studies rely on external dictionaries for sentiment analysis. Jegadeesh and Wu (2013) instead built models using regression-based, word-specific weights estimated from the sample of documents. Antweiler and Frank (2004) used a generative modeling approach and the views of stock market prognosticators who posted on internet message boards as the text corpus. My project will follow similar framework: first constructing measures of interest based on text data, and then examining the relationship between these measures and other economic outcomes of interest. I also explore the use of the state-of-the-art machine learning technique for natural language processing that takes into account the context for each occurrence of a given word, and demonstrate its advantages over the traditional techniques.

2.3 Data and Experimental Setup

In this section, I describe the text data on opinions about climate change and related actions, the annotation process, and the set of machine learning models used for the task of classification.

Data

I leverage an existing dataset of tweets related to climate change made available by the Runestone Interactive Project.[1] Each observation contains the full text of the tweet, with Emojis excluded. I randomly sample a subset of 1,000 tweets and serve as the annotator to label the data using a three-stage decision tree described below and in figure 2.1. Annotation instructions to a hypothetical annotator about how to assign labels are shown in table 2.1.

In the first stage, I determine whether a tweet implies an attitude of believing in the existence of climate change. There is no clear rule that can be applied generally, but for most of them, it is easy to tell if a human being with common sense reads through the text. Critics of climate change typically make very sarcastic comments, using words like conspiracy or hysteria. However, there are a few cases where climate change supporters are sarcastic about jokes made by climate change critics, and thus careful judgement by the annotator is required.

[1] https://runestone.academy/ns/books/published/fopp/Projects/sentiment$_{a}$*nalysis.html*

For those tweets that are identified as positive (i.e., I{believing that climate change is "real"} = 1) in the first stage, I then determine whether it is related to actions. It could be in the form of directly calling to action, or just sharing information about regulations, development of renewable technology, and so on. In this stage, the majority of tweets are discussion about the causes and consequences of climate change, with no action mentioned, so being negative is the majority class.

Finally, for those that are identified as positive in the second stage, I determine whether the action discussed should be categorized as mitigation or adaptation. My judgement is based on the definition given by IPCC. More specially, if the action discussed targets greenhouse gas (e.g., carbon dioxide and methane), including emission reduction, carbon capture or renewable energy, then it is mitigation. If the action discussed does not explicitly aim to affect the climate change process, but instead focuses on modifying human behavior or local environment, then it is adaptation.

Table 2.2 summarizes the data. In the full sample, about 20% of tweets are categorized as dismissing climate change and 80% recognize its existence. In the labeled sample, the ratio is about the same as in the full sample. Among climate supporters, about 30% of them mention actions, and among those, about 20% can be categorized as adaptation.

Model Description

To carry out the experiments, I explore three different machine learning approaches for multi-class text classification tasks in natural language processing: a traditional approach as the benchmark, and two deep learning approaches based on non-contextual (word-based) embeddings and on contextual embeddings.

For the traditional approach, I use logistic regression with a simple bag-of-words representation. Comparing to other models such as decision tree, Support Vector Machine (SVM) and K-Nearest Neighbour (KNN), logistic regression has lower variance albeit higher bias, and it is widely used in many classification tasks. It can also return a probability distribution over all classes instead of a single class as the output. For deep learning approach based on word-based embeddings, I use the convolutional neural network (CNN) for sentence classification (Kim 2014) which consists of a max pooling function and convolution of three window sizes (2, 3 and 4)[2], and the 50-dimensional GloVe vectors trained on 27B tokens as embeddings.[3].

[2] In theory, window numbers and sizes are hyperparameters that can be tuned. Here, since my main goal is to compare different models instead of optimizing the performance of a specific predictive model, I leave this as a future exercise. Moreover, these window sizes should be able to capture a lot of information from phrases, if those are important for distinguishing different classes of tweets.

[3] I keep only the 100k most frequent words and treat the rest as unknown words. This set of words contains the majority of key words for climate change studies, including "climate", "change", "global", "warming", "natural", "disaster", "adaptation", "carbon", "wildfire", "flooding", "hurricane", "storm", "glacier", and "drought", but "mitigation" and "emission" are not in the set.

For deep learning approach based on contextual embeddings, I use the pre-trained, cased BERT-Base (Devlin et al. 2019)

For model training in the experiment, I follow standard practices. I randomly split the dataset into 80-20(%) for train-test set respectively.[4] I use the library PyTorch (Paszke et al. 2019) for implementation of all three models. For optimization, I use the Adam optimizer (Kingma and Ba 2017) with a learning rate (lr) of 0.001, a regularization (weight decay) of 0.00001, a mini-batch of size 32 and a number of epochs of 100.

2.4 Experiments and Results

Two-Class Prediction

I start by training three different sets of models to separately predict binary indicators of (a) whether a twitter believes climate change is ”real”; (b) whether climate change believers mention any action; (c) whether the action mentioned is categorized as mitigation or adaptation. Table 2.3 presents a range of evaluation metrics on the 20% test set.

Panel A are results of predicting climate change beliefs (only metrics for the ”True” class are shown). The results indicate that a simple logistic regression with bag-of-words representation has already achieved a relatively high F1 score and accuracy. CNN achieves slightly higher F1 score and accuracy, and BERT again marginally improve both metrics. It is worth noting that although the overall performance of BERT is the best, it does not necessarily achieve the highest recall. This may not be a main drawback in our context if the ultimate goal is to extract useful information about climate opinions from tweets rather than identifying tweets that fall into a specific class.

Panel B are results of predicting climate change actions among observations that are labeled as positive in the first stage of annotation. Similar patterns are seen in this experiment, although the general level of all metrics is lower. Moreover, BERT makes more significant improvement compared to CNN, underlying the importance of in-depth contextual knowledge in this task.

Panel C are results of predicting whether the climate change action should be categorized as mitigation or adaptation, among observations that are labeled as positive in the second stage of annotation. In this case, logistic regression and CNN have similar performance, and BERT performs worse than the former two. This could be due to fact that the labeled sample is too small for training an effective deep learning model, or that the nature of the task make it sufficient to feature-based logistic regression. While Panel C has the highest

[4] In theory, I can also conduct 5-fold cross-validation and average the results to reduce uncertainty from random splitting. However, given that training one instance of the BERT model is very time consuming, I leave this as a future exercise.

level of accuracy in general, it features the lowest level of recall. This could be a problem if the resulting data is used to study topics related to adaptation, as a significant number of tweets about adaptation are not identified.

Three-Class Prediction

In this experiment, I jointly predict labels generated in the first two stages of annotation. The combination of two binary classes results in three new classes: (1) doubt about the existence of climate change; (2) believing in the existence of climate change but no action mentioned; (3) mentioning climate change actions.

The advantage of this approach is to combine uncertainty in both stages and simultaneously optimize the parameters, resulting in a more efficient model. It also makes prediction errors more interpretable. However, it may bring about new issues of unbalanced classes.

Table 2.4 shows the metrics of precision, recall and F1 score for each class, and accuracy for each model. In this case, believing in the existence of climate but no action mentioned is the majority class, and unbalance does not seem to be a big issue. Again, BERT achieves better performance than logistical regression and CNN. Comparing to accuracy of single-stage models in Panel A and B of Table 2.3, the overall accuracy of the joint model is lower, but it is still higher than the simple product of the accuracy in the two single-stage models, reflecting the accumulation of prediction errors over different stages and the advantage of joint optimization.

Four-Class Prediction

Lastly, I run the experiment of jointly predicting labels generated in all three stages. The four new classes are (1) doubt about the existence of climate change; (2) believing in the existence of climate change but no action mentioned; (3) mentioning mitigation; (4) mentioning adaptation.

Table 2.5 shows the metrics of precision, recall and F1 score for each class, and accuracy for each model. Similar to patterns seen in previous tables, BERT gives the highest accuracy and overall highest level of other metrics for each class. However, the power of using a more complicated model or incorporating context knowledge into the prediction of adaptation is less clear, as the metrics for the class of mentioning adaptation are the same for all three different models.

Unbalance now seems to be an issue here, as the minority class, mentioning adaptation, has less than 1/10 of observations of the majority class, believing in the existence of climate change but no action mentioned. Therefore, I run two additional experiments that down-sample (to match the majority classes) or up-sample the original sample. In particular, one experiment randomly draws 43 observations, without replacement, for each of the first three classes and combines them with the fourth class, while another experiment randomly draws, with replacement, 250 observations from each of the class.

Table 2.6 and 2.7 show the evaluation metrics for the same set of models, and addressing unbalance with down-sampling and sub-sampling, respectively. In the down-sampling case, the overall accuracy actually drops. However, the precision and F1 score for the class of adaptation increase substantially, and CNN performs the best among the three models. BERT's performance is worse than the other two model, likely because the sample is too small for training an effective deep learning model.

In the up-sampling case, performances of all three models for all four classes improve. BERT is again the best model, and the F1 scores for all four classes attain the highest level so far, comparing to both single-stage and joint models. However, one caveat is that the issue of overfitting, especially to the minority class, may be amplified, and using train-test split and cross-validation will not help. This is due to the fact each observation in the minority class has a much higher weight of being sampled, and therefore it is likely to be sampled multiple times and appear in both the train and the test set.

2.5 Discussion

Limitations

While textual analysis has a lot of benefits compared to traditional surveys, there are several limitations.

First, it may not reveal enough information on the specific topic that the researcher cares about. Unlike in an interview or survey, twitters are not directed by certain questions when they post their tweets, so what appears in a single tweet is not predictable and may or may not be relevant. For example, if the research goal is to understand how risk and time preference affect the choice of climate actions, then a structured survey that elicits these parameters directly will be more efficient. At the end of the day, textual analysis is about replacing human judgement by algorithms. If the annotator can read off limited information from the tweet, even a very advanced algorithm can do no better than this.

In addition, the approach used in this study is more suitable for investigation of the "extensive margin" than "intensive margin". For the annotator, it is easier to decide whether a tweet is for or against climate actions, but much harder to scale the intensity of the opinion. Even if it is possible, there may be substantial noise generated in the annotation process. One potential solution is to have more than one annotator, which could to some extent alleviate the problem by providing measures of consistency and agreement.

Finally, twitters are themselves a non-random group of subjects in the population. They are in general younger, more familiar with modern technology, and have the tendency to openly express their thoughts. Therefore, to obtain measures of opinions toward climate actions that are representative for the entire population, stratified surveys are preferred.

Possible Extensions and Applications

As a next step, the trained models can be applied to a large set of tweet data obtained using Twitter's API. A typical tweet is time-stamped, so the resulting predictions can be combined with the timing of high profile events such as release of new IPCC reports or announcement of new climate programs to look at how such events affect individuals' perception.

For a subset of tweets, it is possible to further extract the information on geo-location. Therefore, the resulting predictions can form a panel data and be linked to existing data sets for econometric analysis. One possible application is to aggregate the model outputs to county-year level to construct a local sentiment index for adaptation, and examine its correlation with actual adaptation investments.

Moreover, it will be valuable to compare and relate these data generated from tweets to other forms of data such as survey, interview, newspaper, and documents. From a statistical perspective, different forms of data may contain different signals and have different signal-to-noise ratios. Besides, they may reflect different stakeholders' opinions, in a more subjective or objective way.

This could also be an exercise of cross-validation. For instance, Yale Climate Opinion Maps[5] provides a panel data on climate opinions based on large-scale survey, which can be used as a benchmark of how well tweets can pick up useful signals. Additionally, it would be interesting to design an experiment to ask subjects to both respond to surveys and write tweets about climate actions. The resulting data can be used to train a better model since we will have direct information about the opinion of the twitter in this case.

2.6 Conclusion

As climate change gives rise to challenges to the well-being of both mankind and the ecosystem, taking actions to either slow down the process or directly reduce damage is more pressing than ever. The difficulty in winning political supports for domestic carbon policies and reaching international agreement on emission reduction targets, as well as insufficient climate adaptation, underscores the importance of understanding economic agents' opinions in order to find solutions to expedite climate actions.

This research contributes to the goal by analyzing tweet data and exploring traditional and newly developed machine learning techniques for classifying these tweets along the dimen-

[5] https://climatecommunication.yale.edu/visualizations-data/ycom-us/

sions of climate change belief, attention to actions and inclination to mitigation or adaptation. Different model specifications are explored and evaluated. Experiments show promising results. With only 1,000 labeled data, the F1 score for each class in a deep learning model ranges between 0.7 and 0.9, and the accuracy is higher than 0.8. Models can be further improved with the issue of unbalance addressed, and the accuracy can reach a level of as high as 0.9. In the future, the trained model can be applied to a larger sample of tweets with additional spatio-temporal information, and the outputs will lay foundations for studies that investigate the relationships between opinions towards climate change actions and other outcomes of interest such as actual adaptation investments or the passing of climate bills.

Figures and Tables

Figure 2.1: Three-Stage Decision Tree for Annotation

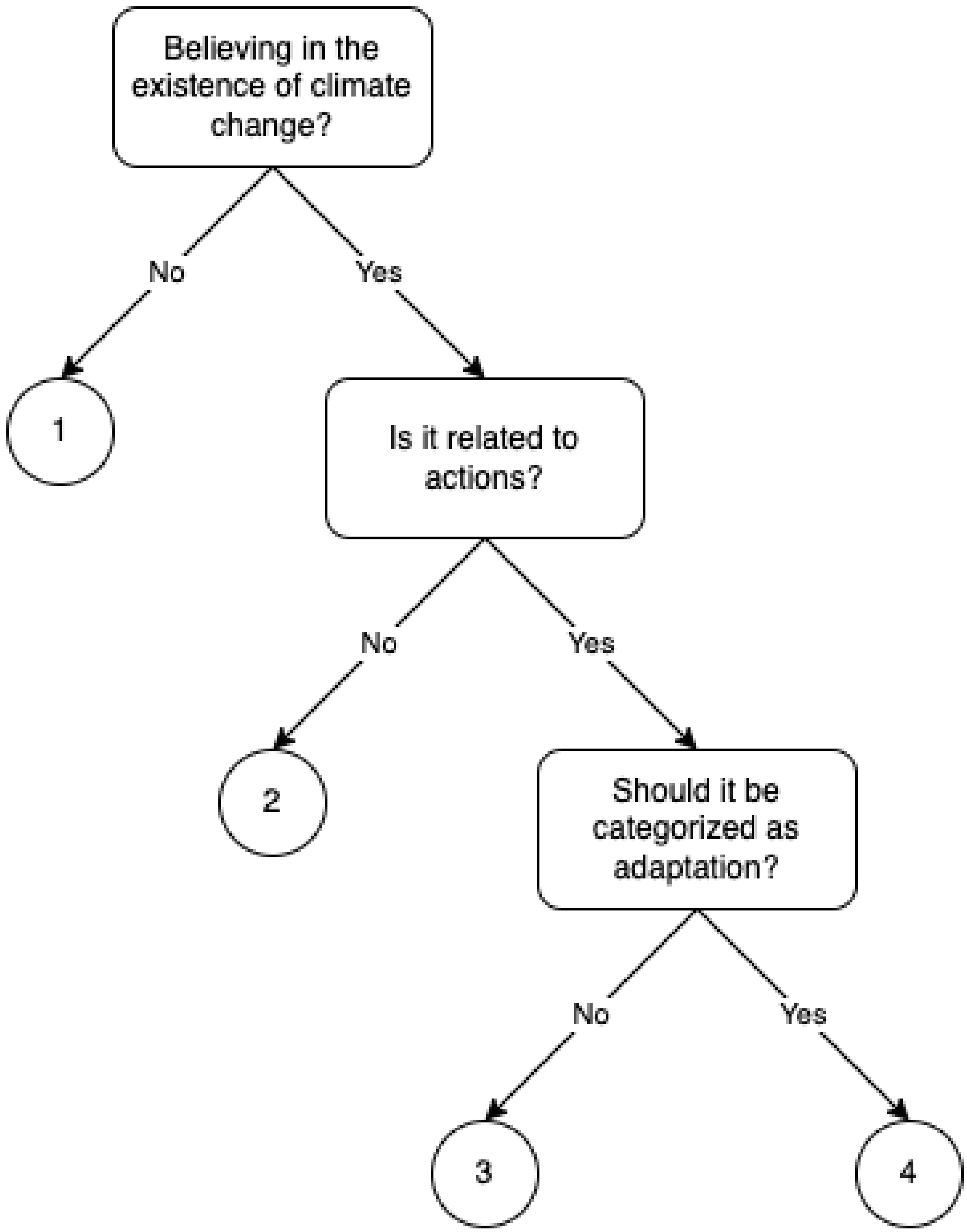


Table 2.1: Annotation Instructions

Labels	Instructions
Real = 0	Sarcasm (e.g. Al Gore; SNObama; scam; ruse; lie; conspiracy; fraud; hysteria; junk science; winter blizzard disproves global warming; “blame” climate change for something irrelevant); question/debate about whether climate change is real
Real = 1 & Action = 0	Causes and consequences of climate change; news about climate change research/people/event
Real = 1 & Action = 1 & Adapt = 0	Emission reduction; carbon capture, including planting trees/protecting forest; CSR; renewable energy; carbon policies/bills/regulation/legislation; ”stop”/”tackle”/”solve” climate change
Real = 1 & Action = 1 & Adapt = 1	Protect/save [someone or something] from [damage]; change [behavior] to avoid [damage]; invest into/build [something] to avert [damage]; migration/relocation

Table 2.2: Data Summary

Dataset	Label	Observations
Full sample	Real = 0	323 (20.64%)
	Real = 1	1242 (79.36%)
Annotated sample	Real = 0	218 (21.8%)
	Real = 1	782 (78.2%)
	Real = 1 & Action = 0	548 (70.08%)
	Real = 1 & Action = 1	234 (29.92%)
	Real = 1 & Action = 1 & Adapt = 0	191 (81.62%)
	Real = 1 & Action = 1 & Adapt = 1	43 (18.38%)

Table 2.3: Performance of Two-Class Models

	LogReg	CNN	BERT
	Panel A: real or not		
Precision	0.894	0.905	0.938
Recall	0.956	0.962	0.943
F1 Score	0.924	0.933	0.940
Accuracy	0.875	0.890	0.905
No. of obs. (% of positive)	1000 (78.20%)		
	Panel B: action or not		
Precision	0.743	0.725	0.833
Recall	0.650	0.725	0.875
F1 Score	0.693	0.725	0.854
Accuracy	0.854	0.860	0.924
No. of obs. (% of positive)	782 (29.92%)		
	Panel C: mitigation or adaptation		
Precision	1.000	1.000	0.750
Recall	0.667	0.667	0.500
F1 Score	0.800	0.800	0.600
Accuracy	0.957	0.957	0.915
No. of obs. (% of positive)	234 (18.38%)		

Table 2.4: Performance of Three-Class Models

		LogReg	CNN	BERT	No. of obs.
Real = 0	Precision	0.667	0.784	0.800	218
	Recall	0.585	0.707	0.780	
	F1 Score	0.623	0.744	0.790	
Real = 1 & Action = 0	Precision	0.754	0.816	0.878	548
	Recall	0.860	0.895	0.886	
	F1 Score	0.823	0.854	0.882	
Real = 1 & Action = 1	Precision	0.853	0.789	0.822	234
	Recall	0.644	0.667	0.822	
	F1 Score	0.734	0.723	0.822	
	Accuracy	0.755	0.805	0.850	

Table 2.5: Performance of Four-Class Models

		LogReg	CNN	BERT	No. of obs.
Real = 0	Precision	0.686	0.757	0.794	218
	Recall	0.585	0.683	0.659	
	F1 Score	0.632	0.718	0.720	
Real = 1 & Action = 0	Precision	0.754	0.818	0.852	548
	Recall	0.886	0.868	0.912	
	F1 Score	0.815	0.843	0.881	
Real = 1 & Action = 1 & Adapt = 0	Precision	0.810	0.719	0.765	191
	Recall	0.472	0.639	0.722	
	F1 Score	0.596	0.676	0.743	
Real = 1 & Action = 1 & Adapt = 1	Precision	0.700	0.700	0.700	43
	Recall	0.778	0.778	0.778	
	F1 Score	0.737	0.737	0.737	
	Accuracy	0.745	0.785	0.820	

Table 2.6: Performance of Four-Class Models, Down-Sampling

		LogReg	CNN	BERT	No. of obs.
Real = 0	Precision	0.545	0.667	0.556	43
	Recall	0.857	0.857	0.714	
	F1 Score	0.667	0.750	0.625	
Real = 1 & Action = 0	Precision	0.600	0.667	0.429	43
	Recall	0.300	0.800	0.300	
	F1 Score	0.400	0.727	0.353	
Real = 1 & Action = 1 & Adapt = 0	Precision	0.500	0.500	0.333	43
	Recall	0.600	0.400	0.400	
	F1 Score	0.545	0.444	0.364	
Real = 1 & Action = 1 & Adapt = 1	Precision	0.846	1.000	0.769	43
	Recall	0.846	0.770	0.769	
	F1 Score	0.846	0.870	0.769	
	Accuracy	0.657	0.743	0.571	

Table 2.7: Performance of Four-Class Models, Up-Sampling

		LogReg	CNN	BERT	No. of obs.
Real = 0	Precision	0.868	0.839	0.870	250
	Recall	0.885	0.904	0.904	
	F1 Score	0.876	0.870	0.887	
Real = 1 & Action = 0	Precision	0.745	0.786	0.833	250
	Recall	0.826	0.717	0.761	
	F1 Score	0.784	0.750	0.795	
Real = 1 & Action = 1 & Adapt = 0	Precision	0.840	0.852	0.889	250
	Recall	0.778	0.852	0.889	
	F1 Score	0.808	0.852	0.889	
Real = 1 & Action = 1 & Adapt = 1	Precision	1.000	1.000	0.960	250
	Recall	0.958	1.000	1.000	
	F1 Score	0.979	1.000	0.980	
	Accuracy	0.860	0.870	0.890	

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Appendix A

Adaptation Investments, Property Damage and Debt Financing of Local Governments

This appendix contains complementary tables for Chapter 1: Adaptation Investments, Property Damage and Debt Financing of Local Governments.

Table A.1: Effects of Adaptation Investments on Average Borrowing Cost, Alternative Controls

	Average borrowing cost (in log)			
	Year FE	StateXYear FE	State-specific linear time trend	No local economic condition controls
	(1)	(2)	(3)	(4)
New adaptation investments occurred in:				
last 1–5 years	-0.021^{*}	-0.020^{*}	-0.019	-0.026^{*}
	(0.012)	(0.012)	(0.012)	(0.013)
last 6-10 years	-0.016	-0.004	-0.017	-0.022
	(0.015)	(0.013)	(0.015)	(0.016)
last 11-15 years	-0.047^{***}	-0.035^{**}	-0.045^{***}	-0.048^{***}
	(0.015)	(0.015)	(0.015)	(0.015)
last 16-20 years	-0.024	-0.028	-0.033	-0.035
	(0.023)	(0.021)	(0.024)	(0.025)
last 21 or above years	0.003	-0.013	-0.016	-0.016
	(0.034)	(0.025)	(0.030)	(0.032)
Local economic condition controls	X	X	X	
Lagged disaster feature controls	X	X	X	X
County FE	X	X	X	X
Year FE	X			
StateXYear FE		X		
State-specific linear time trend			X	
RegionXYear FE			X	X
Observations	47,974	47,974	47,974	47,974

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. The indicator of "year of initiation of adaptation investment" is based on the fiscal year of the adaptation project documented by FEMA. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.2: Effects of Adaptation Investments on Outstanding Debt, Alternative Controls

	Total outstanding debt (in log)			
	Year FE	StateXYear FE	State-specific linear time trend	No local economic condition controls
	(1)	(2)	(3)	(4)
New adaptation investments occurred in:				
last 1–5 years	0.052	0.070	0.067	0.069
	(0.052)	(0.042)	(0.041)	(0.049)
last 6–10 years	0.018	0.058	0.022	0.029
	(0.067)	(0.058)	(0.058)	(0.065)
last 11–15 years	−0.084	0.005	−0.039	−0.062
	(0.067)	(0.051)	(0.054)	(0.065)
last 16–20 years	−0.062	0.038	0.0004	−0.048
	(0.092)	(0.074)	(0.072)	(0.080)
last 21 or above years	−0.134	−0.075	−0.071	−0.063
	(0.141)	(0.120)	(0.118)	(0.127)
Local economic condition controls	X	X	X	
Lagged disaster feature controls	X	X	X	X
County FE	X	X	X	X
Year FE	X			
StateXYear FE		X		
State-specific linear time trend			X	
RegionXYear FE			X	X
Observations	60,284	60,284	60,284	60,284

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. The indicator of "year of initiation of adaptation investment" is based on the fiscal year of the adaptation project documented by FEMA. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.3: Effects of Adaptation Investments on Property Damage, Alternative Controls

	Property damage (in log)			
	Year FE	StateXYear FE	State-specific linear time trend	No local economic condition controls
	(1)	(2)	(3)	(4)
New adaptation investments occurred in:				
last 1–5 years	-0.129^{**}	-0.012	-0.076	-0.098^{**}
	(0.051)	(0.036)	(0.046)	(0.046)
last 6–10 years	-0.026	0.063	0.009	-0.037
	(0.058)	(0.047)	(0.053)	(0.051)
last 11–15 years	0.004	0.055	0.044	0.012
	(0.052)	(0.057)	(0.052)	(0.052)
last 16–20 years	0.049	0.059	0.066	0.068
	(0.068)	(0.068)	(0.073)	(0.071)
last 21 or above years	-0.086	-0.024	-0.065	-0.072
	(0.087)	(0.089)	(0.086)	(0.092)
Local economic condition controls	X	X	X	
Lagged disaster feature controls	X	X	X	X
County FE	X	X	X	X
Year FE	X			
StateXYear FE		X		
State-specific linear time trend			X	
RegionXYear FE			X	X
Observations	93,870	93,870	93,870	93,870

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. The indicator of "year of initiation of adaptation investment" is based on the fiscal year of the adaptation project documented by FEMA. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.4: Effects of Adaptation Investments on Total FEMA Assistance, Alternative Controls

	Total assistance (in log)			
	Year FE	StateXYear FE	State-specific linear time trend	No local economic condition controls
	(1)	(2)	(3)	(4)
New adaptation investments occurred in:				
last 1-5 years	-0.280^{***}	-0.150^{***}	-0.198^{***}	-0.233^{***}
	(0.049)	(0.032)	(0.043)	(0.044)
last 6-10 years	-0.131^{**}	-0.103^{***}	-0.088^{*}	-0.145^{**}
	(0.057)	(0.038)	(0.047)	(0.054)
last 11-15 years	-0.069	-0.097^{**}	0.018	-0.048
	(0.062)	(0.038)	(0.057)	(0.055)
last 16-20 years	-0.237^{***}	-0.097^{*}	-0.111^{*}	-0.163^{**}
	(0.073)	(0.050)	(0.058)	(0.071)
last 21 or above years	-0.010	-0.018	-0.008	-0.039
	(0.086)	(0.065)	(0.081)	(0.078)
Local economic condition controls	X	X	X	
Lagged disaster feature controls	X	X	X	X
County FE	X	X	X	X
Year FE	X			
StateXYear FE		X		
State-specific linear time trend			X	
RegionXYear FE			X	X
Observations	53,192	53,192	53,192	53,192

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. The indicator of "year of initiation of adaptation investment" is based on the fiscal year of the adaptation project documented by FEMA. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.5: Effects of Adaptation Investments on Zillow Home Value Index, Alternative Controls

	Zillow Home Value Index (in log)			
	Year FE	StateXYear FE	State-specific linear time trend	No local economic condition controls
	(1)	(2)	(3)	(4)
New adaptation investments occurred in:				
last 1–5 years	0.004	-0.007^{***}	-0.005	-0.005
	(0.005)	(0.002)	(0.004)	(0.005)
last 6–10 years	0.005	-0.007^{**}	-0.005	-0.006
	(0.005)	(0.003)	(0.004)	(0.005)
last 11–15 years	0.007	-0.006^{*}	-0.004	-0.004
	(0.007)	(0.003)	(0.004)	(0.005)
last 16-20 years	0.002	-0.008^{*}	-0.010^{*}	-0.012^{**}
	(0.008)	(0.005)	(0.005)	(0.005)
last 21 or above years	0.005	-0.014^{**}	-0.010^{*}	-0.009
	(0.010)	(0.005)	(0.006)	(0.007)
Local economic condition controls	X	X	X	
Lagged disaster feature controls	X	X	X	X
County FE	X	X	X	X
Year FE	X			
StateXYear FE		X		
State-specific linear time trend			X	
RegionXYear FE			X	X
Observations	46,095	46,095	46,095	46,095

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. The indicator of "year of initiation of adaptation investment" is based on the fiscal year of the adaptation project documented by FEMA. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.6: Effects of Adaptation Investments on New Construction, Alternative Controls

	Value of new construction (in log)			
	Year FE	StateXYear FE	State-specific linear time trend	No local economic condition controls
	(1)	(2)	(3)	(4)
New adaptation investments occurred in:				
last 1-5 years	0.042	0.012	0.020	0.043
	(0.032)	(0.024)	(0.026)	(0.034)
last 6-10 years	0.092***	0.067**	0.076***	0.092***
	(0.029)	(0.027)	(0.025)	(0.031)
last 11-15 years	0.082**	0.081**	0.080**	0.080**
	(0.033)	(0.039)	(0.037)	(0.039)
last 16-20 years	0.061	0.089	0.068	0.062
	(0.060)	(0.058)	(0.058)	(0.060)
last 21 or above years	0.117**	0.110*	0.137**	0.157***
	(0.056)	(0.061)	(0.061)	(0.057)
Local economic condition controls	X	X	X	
Lagged disaster feature controls	X	X	X	X
County FE	X	X	X	X
Year FE	X			
StateXYear FE		X		
State-specific linear time trend			X	
RegionXYear FE			X	X
Observations	86,720	86,720	86,720	86,720

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. The indicator of "year of initiation of adaptation investment" is based on the fiscal year of the adaptation project documented by FEMA. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.7: Effects of Adaptation Investments on Outcomes, Alternative Measures

	Panel A: Outcomes (in level)					
	Average borrowing cost (1)	Outstanding debt (2)	Property damage (3)	Total assistance (4)	ZHVI (5)	New construction (6)
New adaptation investments occurred in:						
last 1-5 years	3.577	6,942.889	1,705.031	−2,940.940	2.061**	875.097
	(9.381)	(8,065.841)	(3,116.965)	(1,938.146)	(1.020)	(2,371.255)
last 6-10 years	−3.485	8,949.302	4,985.977	−1,513.836	2.211	4,494.505*
	(8.582)	(9,089.488)	(5,077.481)	(911.973)	(1.458)	(2,600.031)
last 11-15 years	−18.206	20,819.920*	2,869.523	−2,911.933	3.521**	1,373.893
	(11.649)	(10,437.900)	(4,652.304)	(1,907.051)	(1.435)	(2,359.975)
last 16-20 years	−4.913	3,540.640	−3,511.003	−2,811.682	1.848	−1,419.770
	(11.811)	(10,448.040)	(2,888.241)	(1,887.137)	(1.193)	(3,444.848)
last 21 or above years	7.969	3,844.697	13,437.520	−2,262.241	5.675**	10,323.210**
	(17.929)	(16,541.940)	(12,048.080)	(1,858.172)	(2.706)	(4,265.347)
Observations	47,974	60,284	93,870	53,192	46,095	86,720
	Panel B: Scaled outcomes (in level)					
	Interest paid per cap (1)	Outstanding debt per cap (2)	Property damage per cap (3)	Total assistance per cap (4)	HPI (5)	New construction per cap (6)
New adaptation investments occurred in:						
last 1-5 years	−3.502	−19.170	−31.849**	−15.213*	0.664	1.398
	(5.677)	(124.785)	(15.824)	(8.825)	(0.695)	(11.077)
last 6-10 years	−1.634	1.517	−10.177	−12.630	0.711	33.656***
	(4.109)	(105.179)	(16.458)	(8.926)	(0.999)	(9.364)
last 11-15 years	−0.467	9.928	−28.310	−13.033	1.796	22.107***
	(3.606)	(72.924)	(26.028)	(9.319)	(1.273)	(7.777)
last 16-20 years	11.636**	179.177*	−35.752	−10.471	−1.095	6.731
	(5.520)	(91.920)	(23.753)	(7.426)	(1.255)	(16.668)
last 21 or above years	16.741	425.908	108.206*	−0.625	0.079	60.334***
	(12.467)	(335.348)	(54.783)	(6.763)	(2.357)	(21.542)
Observations	48,095	60,284	93,870	53,192	42,506	86,720
Local economic condition controls	X	X	X	X	X	X
Lagged disaster feature controls	X	X	X	X	X	X
County FE	X	X	X	X	X	X
RegionXYear FE	X	X	X	X	X	X

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. The indicator of "year of initiation of adaptation investment" is based on the fiscal year of the adaptation project documented by FEMA. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.8: Effects of Adaptation Investments on Outcomes, Alternative Events

	Panel A: First adaptation event					
	Average borrowing cost	Outstanding debt	Property damage	Total assistance	ZHVI	New construction
	(1)	(2)	(3)	(4)	(5)	(6)
Post first adaptation event	−0.017	0.096	−0.101	−0.215*	0.001	0.103**
	(0.016)	(0.095)	(0.061)	(0.108)	(0.007)	(0.050)
	Panel B: Cumulative Adaptation Event					
	Average borrowing cost	Outstanding debt	Property damage	Total assistance	ZHVI	New construction
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative number of adaptation events	−0.026**	0.014	−0.062	−0.133***	0.00001	0.073**
	(0.010)	(0.052)	(0.040)	(0.037)	(0.003)	(0.029)
Local economic condition controls	X	X	X	X	X	X
Lagged disaster feature controls	X	X	X	X	X	X
County FE	X	X	X	X	X	X
RegionXYear FE	X	X	X	X	X	X
Observations	47,974	60,284	93,870	53,192	46,095	86,720

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.9: Effects of Adaptation Investments on Outcomes, Hazard Mitigation Grant Program Only

	Outcomes (in log)					
	Average borrowing cost	Outstanding debt	Property damage	Total assistance	ZHVI	New construction
	(1)	(2)	(3)	(4)	(5)	(6)
New adaptation investments occurred in:						
last 1-5 years	−0.019	0.088*	−0.107*	−0.175***	0.003	0.047
	(0.013)	(0.051)	(0.055)	(0.054)	(0.004)	(0.034)
last 6-10 years	−0.017	0.063	−0.055	−0.116**	0.001	0.096***
	(0.017)	(0.070)	(0.055)	(0.053)	(0.005)	(0.031)
last 11-15 years	−0.043**	−0.039	0.007	0.009	0.003	0.075*
	(0.016)	(0.075)	(0.057)	(0.064)	(0.005)	(0.040)
last 16-20 years	−0.029	0.002	0.047	−0.099	−0.002	0.056
	(0.025)	(0.090)	(0.070)	(0.067)	(0.005)	(0.061)
last 21 or above years	−0.011	−0.043	−0.125	0.030	−0.00001	0.132**
	(0.034)	(0.131)	(0.084)	(0.084)	(0.006)	(0.055)
Local economic condition controls	X	X	X	X	X	X
Lagged disaster feature controls	X	X	X	X	X	X
County FE	X	X	X	X	X	X
RegionXYear FE	X	X	X	X	X	X
Observations	47,974	60,284	93,870	53,192	46,095	86,720

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. The indicator of "year of initiation of adaptation investment" is based on the fiscal year of the adaptation project documented by FEMA. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.10: Effects of Adaptation Investments on Outcomes, Dropping Outliers

	Average borrowing cost (1)	Outstanding debt (2)	Property damage (3)	Total assistance (4)	ZHVI (5)	New construction (6)
Panel A: Top 1% trimmed						
New adaptation investments occurred in:						
last 1-5 years	−0.024*	0.062	−0.102**	−0.213***	−0.0003	0.040
	(0.012)	(0.049)	(0.048)	(0.041)	(0.004)	(0.034)
last 6-10 years	−0.016	0.028	−0.065	−0.116**	0.001	0.090***
	(0.016)	(0.066)	(0.056)	(0.050)	(0.005)	(0.030)
last 11-15 years	−0.039**	−0.050	−0.026	−0.019	0.004	0.076*
	(0.015)	(0.068)	(0.056)	(0.056)	(0.005)	(0.038)
last 16-20 years	−0.027	−0.057	0.037	−0.144*	−0.002	0.050
	(0.025)	(0.083)	(0.066)	(0.074)	(0.005)	(0.059)
last 21 or above years	−0.014	−0.076	−0.179**	−0.054	−0.002	0.120**
Observations	47,494	59,681	92,931	52,660	45,634	85,852
Panel B: Top 5% trimmed	Average borrowing cost (1)	Outstanding debt (2)	Property damage (3)	Total assistance (4)	ZHVI (5)	New construction (6)
New adaptation investments occurred in:						
last 1-5 years	−0.030**	0.064	−0.045	−0.162***	0.001	0.042
	(0.012)	(0.051)	(0.048)	(0.034)	(0.004)	(0.034)
last 6-10 years	−0.022	0.017	−0.038	−0.098**	0.002	0.088***
	(0.016)	(0.067)	(0.053)	(0.037)	(0.005)	(0.031)
last 11-15 years	−0.041**	−0.075	−0.002	−0.015	0.005	0.073*
	(0.016)	(0.075)	(0.056)	(0.042)	(0.005)	(0.038)
last 16-20 years	−0.030	−0.061	0.036	−0.142**	0.001	0.047
	(0.026)	(0.093)	(0.061)	(0.054)	(0.006)	(0.060)
last 21 or above years	−0.013	−0.059	−0.123	−0.010	−0.001	0.114*
	(0.032)	(0.139)	(0.087)	(0.066)	(0.007)	(0.058)
Observations	45,575	57,269	89,176	50,532	43,790	82,384
Local economic condition controls	X	X	X	X	X	X
Lagged disaster feature controls	X	X	X	X	X	X
County FE	X	X	X	X	X	X
RegionXYear FE	X	X	X	X	X	X

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. The indicator of "year of initiation of adaptation investment" is based on the fiscal year of the adaptation project documented by FEMA. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.11: Effects of Adaptation Investments on Outcomes, Intensive Margin

	Panel A: OLS					
	Average borrowing cost	Outstanding debt	Property damage	Total assistance	ZHVI	New construction
	(1)	(2)	(3)	(4)	(5)	(6)
Log of total adaptation investments occurred in:						
last 1-5 years	-0.004^{*}	0.017^{**}	-0.022^{***}	-0.039^{***}	-0.0004	0.007
	(0.002)	(0.008)	(0.008)	(0.007)	(0.001)	(0.005)
last 6-10 years	-0.004	0.011	-0.011	-0.020^{**}	-0.0003	0.016^{***}
	(0.003)	(0.010)	(0.009)	(0.009)	(0.001)	(0.005)
last 11-15 years	-0.006^{**}	-0.008	-0.005	-0.007	0.0002	0.013^{*}
	(0.003)	(0.010)	(0.009)	(0.009)	(0.001)	(0.006)
last 16-20 years	-0.004	-0.002	0.002	-0.030^{**}	-0.001	0.007
	(0.004)	(0.012)	(0.013)	(0.011)	(0.001)	(0.009)
last 21 or above years	-0.0002	-0.006	-0.031^{*}	-0.003	-0.001	0.017^{*}
	(0.006)	(0.021)	(0.016)	(0.014)	(0.001)	(0.009)
	Panel B: IV					
	Average borrowing cost	Outstanding debt	Property damage	Total assistance	ZHVI	New construction
	(1)	(2)	(3)	(4)	(5)	(6)
Log of total adaptation investments occurred in:						
last 1-5 years	-0.003	0.021^{**}	-0.024^{**}	-0.034^{***}	0.001	0.009
	(0.002)	(0.009)	(0.009)	(0.010)	(0.001)	(0.006)
last 6-10 years	-0.004	0.016	-0.015	-0.014	0.0004	0.020^{***}
	(0.003)	(0.013)	(0.010)	(0.010)	(0.001)	(0.006)
last 11-15 years	-0.005^{*}	-0.010	-0.004	0.003	0.001	0.015^{*}
	(0.003)	(0.011)	(0.010)	(0.012)	(0.001)	(0.007)
last 16-20 years	-0.003	-0.002	0.0003	-0.026^{*}	-0.001	0.007
	(0.005)	(0.015)	(0.012)	(0.014)	(0.001)	(0.011)
last 21 or above years	-0.001	0.008	-0.032^{*}	0.004	-0.001	0.024^{**}
	(0.006)	(0.023)	(0.017)	(0.015)	(0.001)	(0.009)
F stat	3875.529	3808.556	4851.308	3915.527	4522.508	4824.751
Local economic condition controls	X	X	X	X	X	X
Lagged disaster feature controls	X	X	X	X	X	X
County FE	X	X	X	X	X	X
RegionXYear FE	X	X	X	X	X	X
Observations	47,974	60,284	93,870	53,192	46,095	86,720

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. The variable of "log of total adaptation investments occurred in last i-j years" is equal to the logarithm of total cost of all adaptation projects initiated between i and j years before the current period. The smallest first-stage F statistics for each model is reported. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.12: Effects of Adaptation Investments on Outcomes, by Initiating Disaster Incident Type

	Outcomes (in log)					
	Average borrowing cost	Outstanding debt	Property damage	Total assistance	ZHVI	New construction
	(1)	(2)	(3)	(4)	(5)	(6)
New adaptation investments induced by hurricanes occurred in:						
last 1-5 years	−0.047*	0.156	−0.221**	0.088	0.032***	0.120**
	(0.024)	(0.125)	(0.096)	(0.124)	(0.011)	(0.058)
last 6-10 years	−0.028	0.130	−0.244**	0.247*	0.025*	0.201**
	(0.024)	(0.124)	(0.111)	(0.140)	(0.014)	(0.096)
last 11-15 years	0.022	0.029	−0.368**	0.067	0.034***	0.187*
	(0.044)	(0.137)	(0.177)	(0.184)	(0.011)	(0.102)
last 16-20 years	0.096*	0.231*	−0.341	0.079	−0.005	0.039
	(0.057)	(0.134)	(0.232)	(0.242)	(0.012)	(0.072)
last 21 or above years	0.084	0.151	−0.132	0.272	−0.007	0.239***
	(0.079)	(0.170)	(0.248)	(0.250)	(0.016)	(0.084)
New adaptation investments induced by floods occurred in:						
last 1-5 years	−0.037*	−0.006	−0.018	−0.267***	−0.010*	−0.002
	(0.021)	(0.080)	(0.071)	(0.075)	(0.005)	(0.039)
last 6-10 years	−0.013	−0.002	0.017	−0.077	−0.017***	−0.006
	(0.020)	(0.084)	(0.086)	(0.106)	(0.006)	(0.041)
last 11-15 years	−0.030	−0.044	−0.131*	−0.030	0.008	0.043
	(0.023)	(0.122)	(0.076)	(0.086)	(0.007)	(0.054)
last 16-20 years	−0.027	−0.109	0.034	−0.091	0.019**	0.002
	(0.027)	(0.118)	(0.126)	(0.126)	(0.009)	(0.079)
last 21 or above years	−0.024	−0.098	−0.326*	−0.086	0.014**	0.091
	(0.039)	(0.197)	(0.170)	(0.118)	(0.007)	(0.084)
New adaptation investments induced by storms occurred in:						
last 1-5 years	0.003	0.015	−0.107*	−0.227***	−0.005	0.025
	(0.015)	(0.080)	(0.059)	(0.061)	(0.005)	(0.026)
last 6-10 years	−0.019	−0.019	0.058	−0.117*	−0.0002	0.051*
	(0.022)	(0.094)	(0.065)	(0.062)	(0.006)	(0.029)
last 11-15 years	−0.049**	−0.083	0.065	0.010	−0.012*	0.009
	(0.022)	(0.107)	(0.078)	(0.068)	(0.006)	(0.037)
last 16-20 years	−0.048	−0.052	0.121	−0.101	−0.011	0.074
	(0.037)	(0.142)	(0.112)	(0.081)	(0.007)	(0.055)
last 21 or above years	0.016	−0.045	0.015	0.067	−0.010	0.081
	(0.045)	(0.150)	(0.167)	(0.135)	(0.008)	(0.079)
New adaptation investments induced by earthquakes occurred in:						
last 1-5 years	−0.060	0.077	0.388	−0.514***	−0.034	−0.212**
	(0.077)	(0.139)	(0.496)	(0.153)	(0.031)	(0.084)
last 6-10 years	0.095	0.189	0.051	−0.148	0.007	−0.094
	(0.095)	(0.213)	(0.329)	(0.242)	(0.031)	(0.117)
last 11-15 years	0.113	0.510*	0.345	−0.008	0.052	−0.333***
	(0.080)	(0.267)	(0.272)	(0.230)	(0.031)	(0.110)
last 16-20 years	0.133	0.306	−0.076	−0.578	0.025	−0.345***
	(0.106)	(0.266)	(0.280)	(0.452)	(0.034)	(0.126)
last 21 or above years	−0.014	0.411	0.002	0.259	0.008	−0.125
	(0.097)	(0.348)	(0.384)	(0.521)	(0.040)	(0.150)

Effects of Adaptation Investments on Outcomes, by Initiating Disaster Incident Type (Continued)

	Outcomes (in log)					
	Average borrowing cost	Outstanding debt	Property damage	Total assistance	ZHVI	New construction
	(1)	(2)	(3)	(4)	(5)	(6)
New adaptation investments induced by fires occurred in:						
last 1-5 years	0.082**	0.418**	0.256*	0.186	−0.008	−0.016
	(0.035)	(0.201)	(0.141)	(0.178)	(0.013)	(0.069)
last 6-10 years	0.036	0.336	0.294	0.347**	−0.014	−0.093
	(0.055)	(0.342)	(0.261)	(0.142)	(0.017)	(0.120)
last 11-15 years	0.097	−0.159	0.481	0.302	0.015	−0.037
	(0.096)	(0.705)	(0.420)	(0.471)	(0.019)	(0.196)
last 16-20 years	0.022	−0.122	0.399	0.516	0.005	−0.211
	(0.190)	(0.761)	(0.614)	(0.331)	(0.033)	(0.341)
last 21 or above years	0.245**	0.038	−0.142	0.245	0.066*	−0.543
	(0.097)	(0.411)	(0.306)	(0.433)	(0.033)	(0.497)
New adaptation investments induced by other incidents occurred in:						
last 1-5 years	−0.008	0.042	−0.126	−0.156**	−0.007	−0.017
	(0.022)	(0.102)	(0.099)	(0.064)	(0.005)	(0.037)
last 6-10 years	−0.041	−0.006	−0.084	−0.184**	−0.006	0.063
	(0.030)	(0.115)	(0.118)	(0.086)	(0.008)	(0.045)
last 11-15 years	−0.040	0.080	0.070	0.274*	−0.009	0.028
	(0.031)	(0.125)	(0.085)	(0.161)	(0.012)	(0.064)
last 16-20 years	−0.078	0.123	−0.139	0.153	−0.038*	−0.102
	(0.059)	(0.165)	(0.137)	(0.131)	(0.021)	(0.075)
last 21 or above years	−0.118	−0.039	−0.023	0.129	−0.020	−0.072
	(0.086)	(0.282)	(0.248)	(0.218)	(0.017)	(0.156)
Local economic condition controls	X	X	X	X	X	X
Lagged disaster feature controls	X	X	X	X	X	X
County FE	X	X	X	X	X	X
RegionXYear FE	X	X	X	X	X	X
Observations	47,974	60,284	93,870	53,192	46,095	86,720

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. The indicator of "year of initiation of adaptation investment" is based on the fiscal year of the adaptation project documented by FEMA. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.13: Effects of Adaptation Investments on Average Borrowing Cost, Heterogeneity

	By decade			Distance to coastline		Pre-existing PDD frequency		Pre-existing per cap housing stock	
	89-98	99-08	09-18	Bottom 50%	Top 50%	Bottom 50%	Top 50%	Bottom 50%	Top 50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
New adaptation investments occurred in:									
last 1-5 years	−0.011	−0.019	−0.012	−0.007	−0.030*	−0.014	−0.030	−0.012	−0.029
	(0.024)	(0.018)	(0.028)	(0.025)	(0.016)	(0.021)	(0.019)	(0.014)	(0.020)
last 6-10 years	0.049	−0.018	−0.029	−0.014	−0.013	−0.043	−0.001	−0.019	−0.016
	(0.043)	(0.019)	(0.037)	(0.021)	(0.017)	(0.026)	(0.017)	(0.014)	(0.026)
last 11-15 years		−0.041	−0.034	−0.042	−0.049***	−0.054**	−0.042**	−0.025	−0.063***
		(0.026)	(0.021)	(0.030)	(0.015)	(0.024)	(0.020)	(0.026)	(0.018)
last 16-20 years		−0.026	−0.013	−0.028	−0.029	−0.056	−0.011	−0.032	−0.021
		(0.047)	(0.031)	(0.048)	(0.026)	(0.040)	(0.027)	(0.033)	(0.037)
last 21 or above years			−0.013	0.042	−0.042**	−0.019	−0.006	−0.006	0.009
			(0.035)	(0.051)	(0.020)	(0.042)	(0.038)	(0.041)	(0.048)
Local economic condition controls	X	X	X	X	X	X	X	X	X
Lagged disaster feature controls	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
RegionXYear FE	X	X	X	X	X	X	X	X	X
Observations	15,579	15,308	17,087	20,742	27,232	24,275	23,699	23,912	24,062

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. The indicator of "year of initiation of adaptation investment" is based on the fiscal year of the adaptation project documented by FEMA. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.14: Effects of Adaptation Investments on Outstanding Debt, Heterogeneity

	By decade			Distance to coastline		Pre-existing PDD frequency		Pre-existing per cap housing stock	
	89-98	99-08	09-18	Bottom 50%	Top 50%	Bottom 50%	Top 50%	Bottom 50%	Top 50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
New adaptation investments occurred in:									
last 1-5 years	0.083	0.025	0.052	0.173**	−0.004	0.129**	0.018	0.083	0.056
	(0.076)	(0.054)	(0.060)	(0.080)	(0.047)	(0.058)	(0.057)	(0.072)	(0.056)
last 6-10 years	−0.057	−0.009	0.059	0.255**	−0.130**	0.230***	−0.132	0.037	0.032
	(0.131)	(0.058)	(0.050)	(0.108)	(0.059)	(0.072)	(0.083)	(0.087)	(0.068)
last 11-15 years		−0.085	−0.021	0.109	−0.123**	0.045	−0.130*	−0.015	−0.082
		(0.086)	(0.060)	(0.114)	(0.058)	(0.101)	(0.074)	(0.087)	(0.076)
last 16-20 years		−0.013	−0.018	0.087	−0.063	0.106	−0.141	0.159	−0.204*
		(0.149)	(0.065)	(0.136)	(0.079)	(0.100)	(0.120)	(0.098)	(0.117)
last 21 or above years			−0.096	−0.125	−0.078	0.072	−0.150	−0.080	−0.074
			(0.088)	(0.244)	(0.107)	(0.155)	(0.192)	(0.175)	(0.151)
Local economic condition controls	X	X	X	X	X	X	X	X	X
Lagged disaster feature controls	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
RegionXYear FE	X	X	X	X	X	X	X	X	X
Observations	20,310	19,017	20,957	29,763	30,521	31,437	28,847	31,150	29,134

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. The indicator of "year of initiation of adaptation investment" is based on the fiscal year of the adaptation project documented by FEMA. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.15: Effects of Adaptation Investments on Property Damage, Heterogeneity

	By decade			Distance to coastline		Pre-existing PDD frequency		Pre-existing per cap housing stock	
	89-98	99-08	09-18	Bottom 50%	Top 50%	Bottom 50%	Top 50%	Bottom 50%	Top 50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
New adaptation investments occurred in:									
last 1-5 years	−0.120	−0.173**	−0.077	0.010	−0.191***	−0.154***	−0.091	−0.044	−0.113*
	(0.100)	(0.084)	(0.082)	(0.071)	(0.059)	(0.055)	(0.065)	(0.061)	(0.057)
last 6-10 years	−0.027	−0.100	−0.009	0.006	−0.108*	−0.056	−0.082	0.007	−0.088
	(0.208)	(0.107)	(0.115)	(0.074)	(0.061)	(0.078)	(0.067)	(0.066)	(0.073)
last 11-15 years		0.061	−0.045	−0.002	−0.037	0.005	−0.043	−0.015	−0.013
		(0.103)	(0.095)	(0.076)	(0.074)	(0.082)	(0.068)	(0.064)	(0.064)
last 16-20 years		0.284	0.147	0.015	−0.025	0.050	0.012	−0.037	0.103
		(0.176)	(0.115)	(0.116)	(0.079)	(0.095)	(0.098)	(0.089)	(0.093)
last 21 or above years			0.108	−0.187	−0.122	0.059	−0.265**	−0.148	−0.081
			(0.122)	(0.142)	(0.111)	(0.132)	(0.124)	(0.115)	(0.114)
Local economic condition controls	X	X	X	X	X	X	X	X	X
Lagged disaster feature controls	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
RegionXYear FE	X	X	X	X	X	X	X	X	X
Observations	31,290	31,290	31,290	46,560	46,620	53,670	40,200	45,720	45,720

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. The indicator of "year of initiation of adaptation investment" is based on the fiscal year of the adaptation project documented by FEMA. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.16: Effects of Adaptation Investments on Total FEMA Assistance, Heterogeneity

	By decade		Distance to coastline		Pre-existing PDD frequency		Pre-existing per cap housing stock	
	99-08	09-18	Bottom 50%	Top 50%	Bottom 50%	Top 50%	Bottom 50%	Top 50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
New adaptation investments occurred in:								
last 1-5 years	−0.043	−0.131**	−0.179***	−0.231***	−0.283***	−0.131**	−0.101	−0.233***
	(0.125)	(0.056)	(0.056)	(0.053)	(0.053)	(0.056)	(0.083)	(0.049)
last 6-10 years	−0.006	0.028	−0.084	−0.175***	−0.183***	−0.026	−0.076	−0.154**
	(0.123)	(0.071)	(0.083)	(0.063)	(0.064)	(0.061)	(0.069)	(0.063)
last 11-15 years	0.040	0.082	−0.012	−0.066	−0.003	−0.005	0.111	−0.118*
	(0.129)	(0.099)	(0.060)	(0.070)	(0.090)	(0.067)	(0.095)	(0.068)
last 16-20 years	0.292	−0.068	−0.033	−0.223**	−0.223**	0.012	0.081	−0.258***
	(0.244)	(0.107)	(0.082)	(0.096)	(0.100)	(0.062)	(0.090)	(0.091)
last 21 or above years		−0.014	−0.149	0.049	0.115	−0.019	0.110	−0.029
		(0.108)	(0.111)	(0.108)	(0.086)	(0.099)	(0.117)	(0.097)
Local economic condition controls	X	X	X	X	X	X	X	X
Lagged disaster feature controls	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X
RegionXYear FE	X	X	X	X	X	X	X	X
Observations	21,902	31,290	26,384	26,417	30,412	22,780	25,907	25,908

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. The indicator of "year of initiation of adaptation investment" is based on the fiscal year of the adaptation project documented by FEMA. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.17: Effects of Adaptation Investments on Zillow Home Value Index, Heterogeneity

	By decade			Distance to coastline		Pre-existing PDD frequency		Pre-existing per cap housing stock	
	89-98	99-08	09-18	Bottom 50%	Top 50%	Bottom 50%	Top 50%	Bottom 50%	Top 50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
New adaptation investments occurred in:									
last 1-5 years	−0.003	0.008	−0.006	0.002	−0.003	−0.001	0.0004	−0.005	0.004
	(0.003)	(0.007)	(0.004)	(0.006)	(0.004)	(0.005)	(0.005)	(0.004)	(0.006)
last 6-10 years	0.006	0.011	−0.008*	−0.004	0.002	0.005	−0.005	−0.001	0.0004
	(0.006)	(0.007)	(0.004)	(0.007)	(0.007)	(0.007)	(0.004)	(0.005)	(0.005)
last 11-15 years		0.008	−0.006*	−0.0004	0.003	0.006	0.001	0.001	0.005
		(0.007)	(0.003)	(0.005)	(0.006)	(0.007)	(0.004)	(0.006)	(0.005)
last 16-20 years		0.020*	−0.007*	−0.001	−0.006	−0.004	−0.001	−0.005	−0.002
		(0.011)	(0.004)	(0.006)	(0.007)	(0.007)	(0.005)	(0.008)	(0.005)
last 21 or above years			−0.007	−0.010	0.005	0.002	−0.001	−0.011	0.007
			(0.005)	(0.009)	(0.009)	(0.009)	(0.007)	(0.010)	(0.006)
Local economic condition controls	X	X	X	X	X	X	X	X	X
Lagged disaster feature controls	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
RegionXYear FE	X	X	X	X	X	X	X	X	X
Observations	3,170	16,297	26,628	19,467	26,628	24,627	21,468	22,058	22,948

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. The indicator of "year of initiation of adaptation investment" is based on the fiscal year of the adaptation project documented by FEMA. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Table A.18: Effects of Adaptation Investments on New Construction, Heterogeneity

	By decade			Distance to coastline		Pre-existing PDD frequency		Pre-existing per cap housing stock	
	89-98	99-08	09-18	Bottom 50%	Top 50%	Bottom 50%	Top 50%	Bottom 50%	Top 50%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
New adaptation investments occurred in:									
last 1-5 years	-0.002	0.024	-0.017	0.043	0.041	0.003	0.071^{*}	0.071	0.023
	(0.031)	(0.035)	(0.027)	(0.046)	(0.048)	(0.039)	(0.039)	(0.048)	(0.031)
last 6-10 years	-0.023	0.031	0.047^{*}	0.054	0.127^{***}	0.090^{**}	0.090^{**}	0.139^{***}	0.059^{**}
	(0.040)	(0.031)	(0.027)	(0.043)	(0.042)	(0.035)	(0.038)	(0.050)	(0.028)
last 11-15 years		-0.008	0.059^{**}	0.054	0.117^{*}	0.036	0.112^{***}	0.140^{**}	0.029
		(0.042)	(0.029)	(0.039)	(0.059)	(0.061)	(0.036)	(0.054)	(0.048)
last 16-20 years		-0.067	0.064	0.027	0.104	0.045	0.054	0.092	0.038
		(0.081)	(0.053)	(0.089)	(0.073)	(0.079)	(0.069)	(0.092)	(0.072)
last 21 or above years			0.148^{**}	0.132	0.149^{*}	0.107	0.113^{**}	0.135	0.107
			(0.058)	(0.091)	(0.081)	(0.104)	(0.051)	(0.084)	(0.075)
Local economic condition controls	X	X	X	X	X	X	X	X	X
Lagged disaster feature controls	X	X	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X	X	X
RegionXYear FE	X	X	X	X	X	X	X	X	X
Observations	26,878	29,879	29,963	42,927	43,793	48,585	38,135	43,009	42,029

Notes: Each observation in a regression is a county-year. Data cover 1989-2018. The indicator of "year of initiation of adaptation investment" is based on the fiscal year of the adaptation project documented by FEMA. The indicator of "new adaptation investments occurred in last i-j years" is equal to one if there was any adaptation project initiated between i and j years before the current period. Standard errors clustered by states are in parentheses. *p<0.1; **p<0.05; ***p<0.01.