Nature as a Defense from Disasters: Natural Capital and Municipal Bond Yields

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Abstract

This paper quantifies the value of natural capital for weather disaster mitigation and the impact of protected areas on local economies. Specifically, I investigate how shocks to local natural capital affect municipal bond markets. Using 313 natural capital loss events and extreme weather events, I show that counties with protected areas face lower natural disaster damages and lower cost of debt. The additional damages from natural disasters are estimated at between \$9 and \$23 million. Moreover, the additional cost of debt related to the loss of natural capital can be as high as \$1.1 million for an average bond. The cross-sectional evidence shows that municipal bonds tied to specific infrastructure projects experience a larger yield increase than bonds with more general purposes. In addition, the effects of natural capital loss are not limited to the county with the natural capital. In fact, neighboring counties are also impacted during extreme weather events. Lastly, the results show two macroeconomic costs related to the loss of natural capital: population migration and a decrease in personal income. In particular, counties that are economically dependent on farming are more affected by natural capital loss suggesting significant macroeconomic effects of natural capital loss related to the food supply. Overall, this paper provides evidence supporting nature conservation and highlights the critical role of nature as a shield from natural disasters.

Keywords: Climate Change, Disaster Management, Environmental Valuation, Global Warming, Municipal Bond Market, Municipalities, Natural Disasters, Nature, Rainfall.

JEL classification: G14, H74, Q54, Q56.

I. Introduction

"There is a delight in the hardy life of the open. There are no words that can tell the hidden spirit of the wilderness that can reveal its mystery, its melancholy and its charm. The nation behaves well if it treats the natural resources as assets which it must turn over to the next generation increased and not impaired in value. Conservation means development as much as it does protection."

— Speech by Theodore Roosevelt in Osawatomie, Kansas, August 31, 1910.

Climate change affects people worldwide and it will be a challenge for decades to come even if decisive policies are implemented tempestively. Environmental studies have cemented our understanding of the connection between human activity, global warming, and the increase in natural disasters' strength and frequency (Van Aalst (2006)). For this reason, mitigation strategies are crucial to diminish economic losses due to climate change. A clear example of the importance of mitigation is related to the impact of extreme weather on local economies.

A particular mitigation strategy that many conservation scientists and economists have proposed entails letting nature do its job. Specifically, one of the most efficient and powerful technologies available today to fight global warming is nature conservation. In fact, increasing protected areas (PAs) would significantly decrease global temperatures and limit weather events' damages (Johansson (1994), Renaud et al. (2016), and Narayan et al. (2017)). Of course, increasing nature preservation efforts come at a cost: a clear one being the opportunity cost of utilizing the land for economic activity. Besides, quantifying the economic effect of increasing the PAs is difficult due to problems in valuing natural amenities and related externalities as well as endogeneity issues of hedonic models.

To minimize these concerns, I quantify the economic value of local natural areas or "natural capital" focusing on their mitigation role for weather damages. The natural capital under consideration includes natural areas such as national parks, wilderness areas, and nature reserves located in each county. Specifically, I utilize extreme weather exposure to compare the differences in economic damages, municipal bond yields, population growth, and personal income between counties that experienced a negative shock to their local natural capital and those that did not. In other words, the quasi-experiment setup can be described by the following example. County A and county B have similar characteristics and similar natural capital stock. At time t, county B experiences a loss in natural capital and at time $t + 1$, the two counties experience an extreme weather event.

In light of the evidence from environmental research studies on protected areas, I hypothesize that counties impacted by natural capital loss experience more significant weather damages compared to counties that did not. Consequently, more significant weather damages result in higher borrowing costs for the county. The increased cost of debt could also be due to the increased saliency of local climate risk. To test this hypothesis, I study the importance of PAs with respect to weather damages using a difference-in-difference model and matching techniques that exploit the exogenous shock to the county's natural capital. This analysis shows that counties that experience these shocks report more extensive weather damages of at least \$9.41 million in the post-period.

Next, I analyze the relationship between nature conservation and municipalities' cost of debt using two empirical approaches. Initially, I utilize extreme weather events as exogenous shocks and compare counties that experienced a loss in natural capital and those that did not. The results show that the difference in municipal bond yields before and after a disaster can be as large as 33 basis points. The coefficients are qualitatively similar when including a triple interaction term that considers the intensity of the weather events.

I explore further the aforementioned relationship by examining the direct effects of natural capital loss on municipal bonds. The results show a sharp increase in municipal bond yields after the natural capital loss event without reversal for at least nine years. Again, I provide additional robustness by utilizing a triple interaction term that includes the measure for extreme weather events exposure.

To complement the results from the difference-in-difference estimation, I test the hypotheses presented in this paper using a matching approach. Specifically, using propensity score and exact matches for specific bond and county characteristics, I show that the results are robust and qualitatively similar to the regression approach.

In addition, I exploit the cross-sectional heterogeneity in bonds' use of proceeds to emphasize the importance of mitigation risk. I classify bonds into two categories: physical and non-physical use of proceeds. Using matching strategies, I show that the yields of bonds issued for physical projects in natural capital loss counties increase more than their matched counterfactuals. To diminish the concerns of selection bias, I utilize a strategy inspired by Crabbe and Turner (1995), Bernstein et al. (2019), Larcker and Watts (2020), and Schwert (2020). This empirical approach consists in matching bonds issued by the same county during the same year. This approach eliminates the concerns for unobservable bond-year effects impacting the results. The results are consistent with the rest of the analysis and show that the most affected bonds are those issued for physical projects and issued by counties impacted by a natural capital loss.

The mitigating effect of natural capital is not only benefitting the county that possesses it but also neighboring counties. Using regression and matching approaches, I present this spillover effect of natural capital loss and suggest that the economic relevance of nature extends beyond its boundaries.

Lastly, I study two of the macroeconomic costs related to natural capital loss and the heterogeneous impact across counties. First, I hypothesize that climate risk awareness increases in the residents of counties affected by a natural capital loss. This increased climate risk perception could be due to the increased damages from weather events subsequent to the natural capital loss event. The increase in climate risk could incentivize the residents to move to more "secure" locations. Alternatively, the partial destruction of a protected area could also be a reason for population migration due to the loss of natural beauty. For these reasons, I test if population growth is affected by these events. The results show that population outflow is at least 1.21% higher in treated counties compared to the control group. Second, due to the increase in extreme weather damages, I hypothesize the local personal income also decreases. The results show a decrease in personal income; however, the coefficients are not statistically significant.

The heterogeneity in county economic dependence from a specific sector allows me to study the cross-sectional effect of natural capital loss on local economies. I conjecture that counties more dependent on farming will be affected most due to their exposure to extreme weather and reliance on water. The results for municipal bond yields, personal income, and population growth provide evidence in favor of this conjecture. These latter results suggest that natural capital loss can have significant macroeconomic effects at the national level due to its importance for food production.

In order to estimate the local natural capital loss, I use protected areas downgrading, downsizing, and degazettement (PADDD). I utilize these events as exogenous shocks to natural capital to define the treated counties. In the past decades, PAs have been subject to widespread downgrading, downsizing, and degazettement (loss of legal protection for an entire protected area) that might affect the way nature protects essential habitats as well as contributes to the alleviation of climate change (Kroner et al. (2019), Qin et al. (2019)).[1]

The data on PADDD was collected thanks to the World Wildlife Fund (WWF) and includes, among other information, PADDD events and the PA affected (Mascia et al. (2012) and Conservation International and World Wildlife Fund (2019)). A strand of the conservation literature has investigated these phenomena and the implications for environmental preservation. Mascia and Pailler (2011), Mascia et al. (2012), Forrest et al. (2015), Kroner et al. (2016), and Kroner et al. (2019) describe PADDD events and comment how these events damage biodiversity, increase global warming, and accelerate deforestation. Building

[1] A graphical representation of the PADDD is reported in Figure 1.

on their insights, the analysis in this paper bridges between conservation studies, economics, and finance and measures in economic terms some of the externalities of PADDD: increased weather damages, higher cost of debt, population migration, and lower personal income.

I utilize municipal bond markets for various reasons. First, municipal bond markets provide access to capital for local municipalities and states to fund public projects and infrastructure. Hence, this market is extremely important in terms of GDP growth and local economic prosperity. Second, municipal bonds provide advantages with respect to the empirical approach of this study and the identification of the effects at play. In fact, municipalities, as opposed to firms, cannot move to avoid local risks such as climate change risk. For this reason, this market reflects the present value of future cash flows backing the bonds as well as the possibility of local shocks. Consequently, I can use the municipal bond market to infer the implications on asset prices of nature conservation in relation to the risk of weather disasters. In other words, if climate risk impacts a municipality, then it will impact its future cash flows, i.e., tax revenue and the likelihood that the municipality can repay the bonds issued.

Lastly, the size of this market is around $4 trillion compared to $10.7 trillion of the corporate bond market and $46 trillion of the stock market (Municipal Securities Rulemaking Board (2021), Siblis Research (2021), and SIFMA (2021)). The municipal bond market covers a crucial role and its size testify to its importance for market participants.

This study is the first to quantify the economic value of natural capital on municipal bond markets. Overall, the results provide exciting insights regarding the value of PAs as a mitigating green infrastructure and nature's economic value for the fight against global warming. I show that nature protects counties from more severe weather damages, translating to a lower cost of debt, lower population outflow, and higher personal income, especially for farming communities. This analysis has clear policy implications for local and state governments as it pertains to the importance of nature conservation.

This paper provides a link between conservation and environmental studies to finance and economic research. Previous studies in the conservation literature explored the benefit of protecting nature from human development. Multiple studies have shown that nature can reduce risks from natural disasters, as well as stimulate biodiversity and collect greenhouse gasses from the atmosphere.[2] Ferrario et al. (2014) present compelling evidence that coral reefs provide substantial protection from natural hazards in coastal communities. Also, the importance of mangrooves, floodplains, and forests is highlighted by Sudmeier-Rieux et al. (2013), Murti and Buyck (2014), and Da Silva and Wheeler (2017). Finally, Kousky and Walls (2014), Indaco et al. (2019), Johnson et al. (2020), Nguyen et al. (2020), Rezaie et al. (2020), Walls et al. (2020), and Chang et al. (2021) focus their attention on protected areas and mitigation from hurricanes and floods. Hence, I build upon the findings in this literature and highlight the financial implications for counties relative to their exposure to climate risk.

As it pertains to the economic literature, scholars have studied the short and long-term impact of natural disasters on economies. Recent research shows that natural disasters' adverse effects persist for many years up to at least ten. Among the many papers, a recent study by Jerch et al. (2020) analyzes the implications of hurricane strikes on local governments' revenue, expenditure, and borrowing dynamics. This study shows that hurricanes reduce tax revenues and expenditures and increase the cost of debt. Moreover, these losses are found to be persistent for at least ten years after a hurricane strike. The results provided by Jerch et al. (2020) emphasize the importance of researching mitigating aspects that could decrease the economic damages resulting from extreme weather events.

Another relevant work by Hsiang and Jina (2014) highlights the long-term effects of hurricanes on a country's economy. They provide robust evidence that national incomes decline and do not recover to pre-disaster trends within twenty years. Another socio-economic effect

[2] Wilkie et al. (2006), Hannah (2008), McDonald et al. (2008), Sudmeier-Rieux et al. (2013), Ferrario et al. (2014), Kousky and Walls (2014), Murti and Buyck (2014), Da Silva and Wheeler (2017), Narayan et al. (2017), Indaco et al. (2019), Johnson et al. (2020), Nguyen et al. (2020), Rezaie et al. (2020), Walls et al. (2020), and Chang et al. (2021).

of hurricanes regards migration. In fact, Mahajan and Yang (2020) show that hurricanes in foreign countries cause an increase in migration to the United States. Also, Strobl (2011) provides evidence that economic growth is affected by migration subsequent to a hurricane strike.

With respect to the benefits of adaptation infrastructure, the study by Narayan et al. (2017) shows the importance of nature preservation and its direct impact on weather damages during a hurricane. In particular, the authors analyze Hurricane Sandy and the damages caused by this storm to the northeast coast of the U.S. in 2012. They estimated that coastal wetlands avoid about \$625 million in direct flood damages. This study displays the importance of nature-based solutions for risk mitigation from natural disasters. Another important study by Johnson et al. (2020) shows that the avoided damages from future floods exceed the cost of acquisition and conservation of natural land in floodplains with larger natural areas exceeding costs by a factor of at least five to one.

Human-made infrastructure is also valuable for climate change risk mitigation. In fact, Kelly and Molina (2020) quantify the effect of climate adaptation infrastructure on property prices. They show significant increases in property value after the infrastructure project is complete. Moreover, they estimate \$3 billion in aggregate net benefits from all adaptation projects in Miami-Dade county highlighting the importance of mitigating infrastructure for local economies.[3]

Given the magnitude of the damages created by natural disasters and their longevity, it is crucial to understand the financial implication of mitigation strategies. My paper fills this gap in the literature. The results presented shed light on one of the properties of natural capital and highlight the importance of nature as a mitigating force against weather disasters and the consequent effects on counties' financing costs.

The results reported in this paper also complement the general and growing literature on

[3] Similar insights are discussed in Fell and Kousky (2015), Jin et al. (2015), Barrage and Furst (2019), Kim (2020), and Walsh et al. (2019).

financial assets and climate risk. Scholars have analyzed the relation between environmental risks and the cost of capital (Sharfman and Fernando (2008), Chava (2014), and Delis et al. (2019)), firm valuation (Bansal et al. (2016), Berkman et al. (2019), Hong et al. (2019)), operating performance (Barrot and Sauvagnat (2016) and Addoum et al. (2020)), and corporate policies (Dessaint and Matray (2017)). As capital markets are concerned, climate risk also affects the allocation of credit by banks (e.g., Cortés and Strahan (2017) and Brown et al. (2020)) and the beliefs of institutional investors (Krueger et al. (2020)). In regards to "green" bonds, Baker et al. (2018), Larcker and Watts (2020), and Flammer (2021) provide interesting insights on the pricing of these novel financial instruments. I contribute to this literature by analyzing the value of natural capital that protects local economies from negative shocks from natural disasters.

The insights presented in this paper are in line with Goldsmith-Pinkham et al. (2020) which shows that exposure to sea-level rise (SLR) increases municipal bond yields. Moreover, the study shows that the pricing of SLR risk begins in 2013. This effect might be due to the more extensive media attention as well as the multiple extreme weather events experienced during these years. However, the authors do not find evidence that municipal bond markets consider immediate flood risk.

Lastly, in a recent working paper, Hong et al. (2020) develop a theoretical model that describes the relationship between costly mitigation, beliefs regarding the consequences of global warming, and the impact on capital stock. Also, the authors use their model to estimate the value of seawalls for hurricane protection. The paper provides a theoretical framework that highlights the limitations of competitive markets when considering mitigation expenditure. My analysis integrates the theoretical intuition in Hong et al. (2020) with empirical estimations of the impact of mitigation "infrastructures" on local economies and municipal bonds.

The remainder of the paper is organized as follows. Section II and III, offer some anecdotal evidence related to the importance of protected areas and a brief history of the national parks in the U.S. Section IV provides a description of the data and summary statistics. Section V includes the empirical approach and the results. Finally, Section VI discusses the implications of the study.

II. Anecdotal Evidence of the Importance of Protected Areas

The environmental economics literature has highlighted the importance of nature preservation and its direct impact on weather damages using many of the hurricanes that hit the United States as case studies. The study by Narayan et al. (2017) is a clear example showing that coastal wetlands were able to avoid about $625 million in direct flood damages during Hurricane Sandy.

In some instances, local governments have realized the importance of nature and how it directly impacts their economies. New York prides itself on supplying its citizens one of the highest quality waters in the U.S. New Yorkers have to thank the hills and valleys of the Catskills watershed and the Delaware River. The New York administration has invested around $1.5 billion in green infrastructure to preserve their water supply and protect these lands. On the other hand, gray infrastructure (filtration plants, dams, etc.) would have costed New Yorkers about $8 billion (Tercek and Adams (2013)). Thus, nature not only protects the water cycle efficiently and cost-effectively but also has multiple positive externalities when protected.

The importance of nature is not limited to water. Another clear aspect regards the protection nature provides from weather events and the dire threats of global warming. For instance, in recent years, Iowa started to experience floods like never before in its history and Iowans endured on their skin the issues of climate change. These difficulties ignited a movement that culminated in the passing of the country's largest conservation ballot initiative. This ballot funds the restoration of Iowa's floodplains protecting essential wildlife habitats, reducing water pollution, shielding communities, businesses, and farmlands from floods, and protecting fertile soil. This \$150 million fund will generate enormous societal, economic, and environmental benefits for the people of Iowa (Tercek and Adams (2013)).

Not just governments see nature as an asset to preserve. In 2010, the WWF joined forces with Coca-Cola, which operates 39 bottling plants in China, to improve the water quality of the Yangtze's upper reaches. One of the projects involves searching for ways for the multinational to be more efficient in its own use of water. For continued growth in China, Coca-Cola officials recognize that the company must strengthen what they call "water security." The WWF projects are "not considered philanthropy [or] even CSR" says Brenda Lee, vice president of Coca-Cola China. "It is part of our business commitment. We can only prosper and thrive in communities that are sustainable" (Knowledge@Wharton (2010)). Coca-Cola faces similar challenges in Latin America and the rainforests of these regions are considered important assets for the company. These are only a few examples that describe how crucial it is to preserve natural areas.

A. *Example of PADDD*

One National park affected by PADDD is the Yosemite National Park. The park was first protected in 1864 by a land grant and became a national park in 1890. The park also became a World Heritage Site in 1984 for its geological and ecological values and hosts more than four million tourists every year. The park experienced many legal changes to its boundaries and protection. In fact, the park was downgraded in 1892, 1901, and 1913 for the building of various infrastructures such as wagon roads, turnpikes, electrical lines, and dams. In addition, Yosemite was downsized by 1,309.30 km^2 (505.52 mi^2), which corresponded to 34% of its original size of 3,886 km^2 (1,500 mi^2), in 1905 and 1906 to allow for forestry and mining activities (Kroner et al. (2016). Other legislations partially offset the downsizing by about 293 km^2 (113 mi^2) and created another wilderness area in 1964, amounting to 57% of the downsized land. Currently, the Yosemite National park is 77% of its original size and 19% of the originally protected lands are now under other forms of protection (Kroner et al. (2016)). These legal actions have caused fragmentation in unprotected forests near Yosemite as well as ecosystem damages (Kroner et al. (2016)).

Among the ecosystem damages, PADDD might have affected the park's ability to preserve valuable water resources. In fact, the park hosts the origin of two rivers, Tuolumne and Merced River, which provide clean water to many areas in California. The Tuolumne river alone provides drinking water for over 2.7 million people in the San Francisco Bay area (Tuolumne River Trust (2021)).

III. Short History of National Parks and Protected Areas

On March 1, 1872, President Ulysses S. Grant signed the Yellowstone National Park Protection Act into law, establishing the first national park in the world. In the following years, Theodore Roosevelt became one of the main champions of conservation by tremendously impacting the National Park system. In fact, he doubled the number of sites during his tenure in office and enabled himself and following presidents to proclaim historic landmarks, historic or prehistoric structures, and other objects of historic or scientific interest in federal ownership as national monuments. On August 25, 1916, President Wilson created the National Park Service, responsible for protecting the national parks. Today, the National Park system comprises more than 400 areas covering more than 84 million acres in 50 states, D.C., and territories.

Another important step towards conservation was the enactment of the Uniform Conservation Easement Act. This act authorizes the creation of permanent easements on real property for conservation and historic preservation purposes. Thanks to this act, a landowner is entitled to federal income tax benefits if she decides to register her land as an easement.

IV. Data and Summary Statistics

A. *Weather Damages*

The National Oceanic and Atmospheric Administration (NOAA) collects data on crop and property damage (in U.S. dollars) caused by weather events. I collect this information for the sample period starting in 1969 and ending in 2020.[4] Figure 2 and 3 report the frequency and economic damages (adjusted for inflation) of billion-dollar disaster events by event category in the United States from 1980 to 2020. First, we notice how large disasters have increased in frequency and impact in dollar terms. Moreover, the breakdown by type of events shows that a large portion of the damages is caused by events characterized by heavy precipitation (tropical cyclones).

Table I reports summary statistics related to weather damages. Specifically, we notice that the states impacted the most in absolute dollar terms are Texas, Florida, and Louisiana. These states are often subject to large tropical cyclones and hurricanes, which bring great devastation.

B. *Urban-Rural Classification*

The information regarding the Urban-Rural Classification is collected from the National Center for Health Statistics (NCHS). Counties are classified into six urban-rural categories: large central metropolitan areas, large fringe metropolitan areas, medium metropolitan areas,

[4] The data can be found here: `https://www1.ncdc.noaa.gov/pub/data/swdi/stormevents/csvfiles/`.

small metropolitan areas, micropolitan areas, and noncore. Following are the definitions of these classifications as in Ingram and Franco (2014). Large central metropolitan areas are counties in Metropolitan Statistical Areas (MSAs) with a population of one million or more that contain the entire population of the largest principal city of the MSA, or contain the entire population of the largest principal city of the MSA, or contain at least 250,000 inhabitants of any principal city of the MSA.

Large fringe metropolitan areas are counties in MSAs with a population of at least one million that did not qualify as large central metro counties. Medium metropolitan areas are counties in MSAs with a population of 250,000 to 999,999. Small metropolitan areas are counties in MSAs with a population of less than 250,000. Among the nonmetropolitan categories are micropolitan and noncore. Micropolitan are counties in micropolitan statistical areas. Noncore are nonmetropolitan counties that did not qualify as micropolitan. A micropolitan statistical area must have at least one urban cluster with a population of at least 10,000 but less than 50,000.

C. Protected Area Downgrading, Downsizing, and Degazettement

One of the critical data of this study is the Protected Area Downgrading, Downsizing, and Degazettement (PADDD) data collected by the WWF (Mascia et al. (2012) and Conservation International and World Wildlife Fund (2019)). For this dataset, protected areas are defined following the International Union for Conservation of Nature (IUCN) definition: "A protected area is a clearly defined geographical space, recognized, dedicated, and managed, through legal or other effective means, to achieve the long-term conservation of nature with associated ecosystem services and cultural values" (Dudley (2008)).

Despite a net growth of PAs, research in ecology and conservation has shown widespread and unreported PADDD (Mascia and Pailler (2011), Mascia et al. (2014), Forrest et al. (2015), Pack et al. (2016), Cook et al. (2017), and Kroner et al. (2019)). Downgrading is a decrease in legal restrictions on the number, magnitude, or extent of human activities within a PA. Downsizing is a decrease in the size of a PA as a result of the excision of an area of land or sea area through a legal boundary change. Lastly, degazettement is a loss of legal protection for an entire PA (Mascia and Pailler (2011)).

The PADDD dataset contains 3,700 enacted PADDD events affecting about two million km^2 (0.77 million mi^2) across 73 countries from 1872 to 2018 (Kroner et al. (2019)). The reasons for the enactment of PADDD range from industrial-scale resource extraction and development to land claims and local land pressures. A small fraction of the PADDD is meant for conservation planning (Mascia and Pailler (2011)).

These data are crucial to identify the counties that experience a loss in natural capital. The dataset collected by the WWF provides ArcGIS Pro shapefiles that describe the perimeter of the PA affected by a PADDD event. I use ArcGIS Pro to identify the county in which each protected area resides. This allows me to create a panel of counties affected by PADDD from 1900 to 2018. I restrict the study to the U.S. since the drivers of PADDD across countries might be different and might be influenced by differences in legal framework, economic and political environment, as well as other observable and unobservable circumstances.

Figure 4 and 5 show the location of the PAs that have been downgraded, downsized, or degazetted during the sample period starting from 1976 to 2018. The sample period is limited to these 43 years since the economic data is available starting from 1969 and the first PADDD event after 1969 was enacted in 1976.

Table II provides summary statistics related to the PADDD. We notice that the year with the largest area affected by this phenomenon is 2016, with 31,859 km^2 (12,301 mi^2). This area excludes Alaska and Hawaii. If we include these two states, the area impacted is 103,231 km^2 (39,858 mi^2). 2016 is also the year with the most counties affected by the enactment of a PADDD, followed by 1986, 2011, and 2012. These years also report the largest area affected in the sample period. To better understand the size of the PAs affected, 103,231 km^2 (39,858 mi^2) is about the size of Iceland or the equivalent of eleven Yellowstone National Parks.[5]

It is also interesting to notice that more than half of the PADDD is concentrated in rural areas. In fact, for the period from 1976 to 2017, about 44% (66% including Alaska and Hawaii) of the events and 54% (88%) of the area affected is in urban areas classified as micropolitan or noncore as shown in Table III. The data for the subsample from 2005 to 2017 used for the municipal bond analysis is available in Table IV.

With respect to the geographical distribution of PADDD events, Table V shows that, in the period from 1976 to 2017, the states with the most events are Michigan, Arkansas, California, Florida, and Illinois. Instead, from 2005 to 2017, Arkansas, California, Florida, Washington, and New Mexico report the most events (Table VI). Moreover, 45 of the 48 contiguous states experience at least one PADDD event from 1976 to 2017.

The WWF dataset also includes the reported cause of PADDD. Table VII provides the definitions of each of the causes of PADDD for the sample period from 1976 to 2017. Also, Table VIII highlights how the PADDD events are heterogeneous as it pertains to the reason for the enactment. Specifically, 49% of the area affected by natural capital loss is caused by subsistence, defined as non-commercial or small-scale commercial, artisanal, or non-industrial (non-mechanized) extraction or production activities. Moreover, 33.2% of the area affected is caused by infrastructure projects, mining, and oil and gas extraction. The rest of the PADDD is due to land claims or other reasons. Due to the lack of detailed information, the legal and political procedures that drive the enactment of a PADDD are unclear. However, the downgrade, downsize, or degazettement of a protected area needs to be approved by the federal government.[6]

[5] The largest area impacted of 103,231 km^2 (39,858 mi^2) is not reported in Table II since it includes information on Alaska and Hawaii, which are excluded from this study.

[6] In the appendix, I provide additional discussion regarding why natural capital loss events happen.

D. *Precipitation Data*

To estimate the extreme weather exposure, I utilize the daily precipitation data contained in the Parameter-elevation Regressions on Independent Slopes Model (PRISM). This dataset is publicly available on Dr. Wolfram Schlenker's website of Columbia University.[7] The dataset comprises total precipitation on a 2.5×2.5-mile grid for the contiguous United States from 1950 to 2019.

I use the precipitation data because some of the most frequent and damaging extreme weather events in the past years have been severe storms and tropical cyclones (Smith and Katz (2013), Figure 2, and Figure 3). Those types of weather events come with ample precipitation, which causes, together with storm surges in coastal areas, flooding. Of course, a portion of the damages from these events is caused by high winds. However, strong winds and heavy precipitation usually come together during these weather events. Section V contains a more detailed discussion of the natural disaster exposure measure.

This dataset could be complemented with data on droughts, earthquakes, and other natural disasters that do not involve heavy precipitations. In fact, evidence from environmental studies shows that protected areas are effective in preventing or mitigating hazards associated with droughts and earthquakes, including particularly landslides and rockfalls in mountainous regions (Dudley et al. (2015), Renaud et al. (2016), Dudley and Stolton (2010)).

E. *County Economic and Population Data*

The county-level economic and population data are collected from the Bureau of Economic Analysis (BEA). For this study, I utilize county-level population, personal income, and unemployment rate. The sample period utilized starts in 1969 and ends in 2018. The BEA defines personal income as the income that people get from wages and salaries, Social Security and other government benefits, dividends and interest, business ownership, and other

[7] `http://www.columbia.edu/~ws2162/links.html`.

sources. The employment rate is defined as the ratio of employed people and total labor force. I also collect information on the counties' economic characteristics from the Economic Research Service of the U.S. Department of Agriculture. Specifically, I utilize the 1979, 1986, 1989, 2004, and 2015 County Typology Codes. These codes classify all U.S. counties into six mutually exclusive categories of economic dependence together with other categories of policy-relevant themes. A county can be classified as economically dependent on farming, mining, manufacturing, Federal/State government, recreation, or non-specialized.

F. Municipal Bonds Data

The municipal bond data is collected from the Municipal Securities Rulemaking Board (MSRB). This dataset contains all municipal bond transactions from 2005 to 2020. The variables utilized in this study are the bond yield, coupon rate, years to maturity, and size of the issue. Following Schwert (2017), I utilize only fixed-coupon and tax-exempt bonds that trade at least ten times.[8] This latter specification guarantees some uniformity and a minimum level of liquidity.

In addition, following Chalmers (1998), I exclude trades after a bond's advance refunding date since the bond can be considered risk-free after this point. Next, I exclude the trades in the first three months after issuance and the last year before maturity due to the noisy nature of these periods (Green et al. (2007) and Schultz (2012)). To remove complications with embedded options, I remove callable bonds. I complement the data from MSRB with information regarding bond characteristics from Bloomberg. Specifically, I collect the issuer name, issue size, county of issuance, sources of funds, green bond classification, general obligation (GO) indicator, use of proceeds, credit rating, insurance status, and pre-refunding status and timing. Moreover, I hand-collect the county affiliated to each bond if this information is missing.

[8] I remove federally taxable bonds and bonds eligible for alternative minimum tax (AMT).

Finally, I collect the municipal bonds AAA-rated tax-exempt benchmark curve from 2005 to 2019 from Bloomberg and use it as a benchmark for the municipal bond credit spread analysis.[9] The transaction data from the MSRB, together with the information from Bloomberg and the AAA-rated curve, allow me to construct a monthly panel of volume-weighted yields at the bond level.

Following Green et al. (2010), I clean the data from obvious data errors. Specifically, I eliminate all observations for a bond if the coupon and maturity are missing for all observations. I also remove observations with the coupon recorded as greater than 20%, or if the maturity is recorded as over 100 years. Moreover, I exclude all transactions where the price is less than 50% of face value. Then, I eliminate transactions with prices greater than 150% of face value with a short time to maturity. Lastly, I remove trades recorded after the maturity date. The final sample contains 736,019 transactions for 82,310 bonds.

Following Cantor and Packer (1997), I convert the rating scale to a numeric classification. For example, AAA (Moody's) and Aaa (Fitch and SP) are converted into the value 1, AA+ and Aa1 are classified as 2, AA and Aa2 as 3, and so forth.

Lastly, I classify bonds as "physical" if the use of proceeds mentions a specific infrastructure project. For example, a bond issue that mentions as use of proceeds "water utility" or "highway" will be classified as "physical." On the other hand, a bond that cites as use of proceeds "student loans," "lawsuit," or "refunding" will be classified as "non-physical." This classification is helpful to exploit the cross-sectional heterogeneity in the bonds' use of proceeds and to control for within-county heterogeneity in disaster exposure. Table IX contains a list of the use of proceeds that were classified as "physical" and "non-physical."

[9] The results of the robustness tests using yield spreads are reported in the appendix.

G. *Real Estate Data*

I use data from Zillow to provide robustness to the main analysis. Specifically, I utilize the Zillow Home Value Index (ZHVI) from 1996 to 2020.[10] There are various types of indices available:

- ZHVI All Homes Time Series, Smoothed and Seasonally Adjusted: A smoothed, seasonally adjusted measure of the typical home value and market changes across a given region and housing type. It reflects the typical value for homes in the 35^{th} to 65^{th} percentile range. The raw version of the mid-tier ZHVI time series is also available.
- ZHVI All Homes - Top Tier Time Series, Smoothed and Seasonally Adjusted: typical value for homes within the 65^{th} to 95^{th} percentile range for a given region.
- ZHVI All Homes - Bottom Tier Time Series, Smoothed and Seasonally Adjusted: typical value for homes that fall within the 5^{th} to 35^{th} percentile range for a given region.
- ZHVI Single-Family Homes Time Series.
- ZHVI 1-, 2-, 3-, 4-, and 5+ Bedroom Time Series.

I use the first index listed above for the analysis in the paper.

H. *National, State, and Local Parks*

To ensure that the matching analysis accounts for important observable county characteristics as it pertains to protected areas, I collect the protected area of each county using the Protected Area Database (version 1.4) from the United States Geological Survey.[11] The Protected Areas Database of the United States (PAD-US) is the nation's inventory of protected areas including public open space and voluntarily provided private protected areas.

[10] The data is available at `https://www.zillow.com/research/data/`

[11] `https://www.usgs.gov/core-science-systems/science-analytics-and-synthesis/gap/science/pad-us-statistics-and-reports?qt-science_center_objects=0#qt-science_center_objects`.

The PAD-US provides a series of spatial databases of areas dedicated to the preservation of biological diversity and other natural, recreational or cultural uses, managed for these purposes through legal or other effective means. Most areas are public lands owned in fee; however, long-term easements, leases, and agreements or administrative designations documented in agency management plans may be included.[12] The PAD-US database strives to be a complete "best available" inventory of protected areas (lands and waters), including data provided by managing agencies and organizations.

The PAD-US geodatabase contains the geographic boundaries, the protection mechanism category (e.g., fee, easement, designation, other), owner and managing agency, designation type, unit name, area, public access, and state name in a suite of standardized fields. Moreover, the areas in PAD-US are assigned conservation measures that assess management intent to permanently protect biological diversity using the "GAP Status Code" and the "IUCN Category" standard.

The GAP status code is defined as follows. Status 1: an area having permanent protection from the conversion of natural land cover and a mandated management plan in operation to maintain a natural state within which disturbance events (of natural type, frequency, intensity, and legacy) are allowed to proceed without interference or are mimicked through management. Status 2 represents an area with permanent protection from the conversion of natural land cover and a mandated management plan in operation to maintain a primarily natural state, but which may receive uses or management practices that degrade the quality of existing natural communities, including suppression of natural disturbance. Status 3: an area having permanent protection from the conversion of natural land cover for the majority of the area, but subject to extractive uses of either a broad, low-intensity type (e.g., logging, off-highway vehicle recreation) or localized intense type (e.g., mining). It also confers protection to federally listed endangered and threatened species throughout the area. Status 4: there are no known public or private institutional mandates or legally recognized

[12] The definitions of the protected area categories are reported in Table X.

easements or deed restrictions held by the managing entity to prevent the conversion of natural habitat types to anthropogenic habitat types. The area generally allows conversion to unnatural land cover throughout or management intent is unknown.[13]

Finally, the USGS provides a Flattened Vector Analysis file that includes the spatial information on protected areas together with county boundaries. This file is used to compute the protected area of each county by GAP status code.

This information is extremely important because it allows comparing counties with similar-sized protected areas. Unfortunately, these data can be used only as a time-invariant specification because, as noted by the USGS, the comparison between multiple PAD-US versions with the purpose of comparison is highly discouraged. Many of the changes among versions of the PAD-US are due to improvements to agency and organization GIS systems and data, rather than actual changes in protected area acquisition on the ground. PAD-US includes a date of establishment field defined as the year the protected area was designated, decreed, or otherwise established. Currently, this field is not entirely attributed and data gaps are difficult to address.

To conclude the data and summary statistics section, Table XI contains the summary statistics of most variables utilized in this paper.

V. Empirical Approach

This section describes the empirical approach I utilize to study the importance of natural capital.

[13] `https://www.sciencebase.gov/catalog/item/56bba50ce4b08d617f657956`.

A. Extreme Weather Exposure

In order to estimate the local extreme weather exposure, I utilize precipitation data. The use of precipitation is in line with the evidence from the climatology research that shows increases in precipitation intensity in the contiguous United States due to climate change (e.g., Hennessy et al. (1997), Rosenzweig et al. (2002), and Balling and Goodrich (2011)). Moreover, the economic literature has utilized various physical measures because the use of physical weather characteristics (wind speed, rainfall, or storm surge) is necessary to maintain the exogenous nature of the shock (Noy (2009) and Hsiang and Jina (2014)). Many studies use only hurricanes as natural disasters. However, a measure of extreme events adjusted for local characteristics is necessary to expand the analysis to areas unaffected by large hurricanes. A measure of this type will include smaller-scale events, but these events are still rare and damaging for the locality under consideration.

The extreme weather exposure measure used in this paper is adapted from Jerch et al. (2020). Specifically, I start from the daily precipitation data from the PRISM dataset. First, I average the daily precipitation across all 2.5×2.5-mile grids in the county and subsequently average them together to create a monthly precipitation measure. This latter value needs to be adjusted to account for county-specific weather characteristics. For this reason, I standardize the average monthly precipitation using the monthly mean over the previous ten years and the standard deviation computed over the same period. Next, for each county, I compute the maximum standardized precipitation experienced during each year. Lastly, the extreme weather exposure equals the maximum annual standardized precipitation similar to Jerch et al. (2020).

$$Weather\,Exp._{c,\,t} = max\left(\frac{Precipitation_{c,t} - Average\,Precipitation_{c,1-10}}{St.\,Dev.\,Precipitation_{c,1-10}},\ 0\right) \tag{1}$$

$Weather\ Exp._{c,\,t}$ allows to identify the local shocks caused by extreme weather and study the impact of these events accounting for time-varying county weather characteristics. Another advantage of this measure regards the heterogeneity of natural disaster mitigation across the United States. Specifically, counties around the U.S. are exposed to very different threats from global warming as diverse as wildfires, hurricanes, and droughts. Consequently, each counties' past exposure affects the way they prepare for future events. For instance, Harris County (home to Houston) in Texas is very often exposed to torrential rains as well as tropical storms and hurricanes. On the other hand, El Paso County (Texas) is threatened by severe droughts. These counties have different characteristics as it pertains to weather exposure as well as mitigating infrastructure. The measure I propose in this paper takes into account these regional differences within the state.

Lastly, the use of this locally-adjusted measure is also supported by the environmental literature. In fact, various studies show that rainfall intensity is heterogeneous across counties and there is large spatial heterogeneity in disaster-triggering precipitation thresholds (Balling and Goodrich (2011), Pielke and Downton (2000), and Liu et al. (2020)).

B. Natural Capital Loss and Weather Damages

Economists have considered natural resources as an asset or capital stock that provides a series of services or "income," and the depletion of these resources is related to the depreciation of the natural capital value (Gray (1914) and Barbier (2019)). This natural capital approach formally proposed by Hotelling (1931) became standard in environmental and resource economics.

This study builds on the proposed definition of natural capital and focuses on the analysis of its economic value. The natural capital loss events represent the key to understanding the dynamics between nature and economic outcomes. Hence, the initial analysis consists of investigating the impact of PADDD on counties. Formally, I hypothesize that counties that experienced a loss in natural capital are more vulnerable to damages from weather events. The underlying intuition for this hypothesis is based on the notion that protected areas provide a natural defense mechanism that helps mitigate the destructive strength of natural disasters.[14]

To test this hypothesis, I perform a difference-in-difference analysis that exploits the natural capital loss events as exogenous shocks to the county's natural capital. The outcome variable to be analyzed is the CPI-adjusted annual total property and crop weather damages (log) computed using NOAA data. Following is the model utilized for the estimation of the natural capital effect.

$$\begin{aligned} Damages_{c,\,t} &= \alpha + \gamma_1 Treated \times Post + \gamma_2 Treated + \gamma_3 Post \\ &\quad + \gamma_4 Weather\,Exp_{1-5} + \theta_t{}' X_{i,t-1} + \delta_c + \delta_{s,t} + \epsilon_{c,t}, \end{aligned} \tag{2}$$

where $Damages_{c,t}$ represent the weather damages in county c in year t. $Treated$ is an indicator for a county that has experienced natural capital loss, $Post$ is an indicator that equals one for the period after the natural capital loss event, $Weather\,Exp_{1-5}$ represent the natural disaster exposure from year $t-1$ to $t-5$, and X represent a vector of control variables. Lastly, δ_c and $\delta_{s,t}$ represent the county and state-year fixed-effects, respectively.

The $Weather\,Exp_{1-5}$ is calculated using the maximum standardized precipitation that the county experience from year $t-1$ to $t-5$. The reason for this choice is due to the rare nature of these events. For this analysis, I consider an event window that starts five years before the PADDD event and ends five years after. The controls used are lagged personal income, lagged unemployment rate, population (log), lagged density (log), and an indicator for urban-rural classification (small metro, micropolitan, non-core), and trend variables (changes from $t-2$ to $t-1$) for population, density, personal income, and unemployment

[14] The papers that describe this relationship are mentioned in the introduction.

rate.[15] The coefficient of interest is γ_1. The cohorts are formed using the year of the natural capital loss event. Specifically, I stack the observations using the PADDD year as year zero. This procedure creates 13 cohorts. For this analysis, I excluded large central and fringe metropolitan areas due to the small size of the PAs affected.

The weather damages are correlated with the county's economic activity and, for this reason, endogeneity concerns arise. To diminish these concerns, I control for various county characteristics and pre-trends as specified above. Another important control is the weather exposure which allows me to match counties with respect to their disaster vulnerability. Lastly, I use county and state-year fixed effects to control for unobservable county and state-year characteristics. The county fixed effects reduce the concern that the outcomes reported are not caused by differences in pre-existing disaster mitigation programs implemented by more exposed counties. Moreover, the county fixed effects remove the time-invariant geographical differences across counties that could be related to weather damages (proximity to the ocean, presence of coral reefs and/or protected areas, elevation).

Also, there might be concerns that the extreme weather exposure measure is related to local economic conditions. For this reason, following Bernstein et al. (2019) and Goldsmith-Pinkham et al. (2020), I plot the coefficients of the non-parametric regression between the standardized precipitation exposure deciles and real estate prices. The coefficients are estimated relative to the lowest precipitation exposure decile. I use the Zillow smoothed and seasonally adjusted index for real estate prices. This index represents the typical value of homes in the 35^{th} to 65^{th} percentile range.

Figure 6 shows that there is no relation between the extreme weather measure and real estate prices, which proxy for local economic conditions. For this reason, the county level estimation should not be affected by endogeneity bias and identification can be performed within the state. These results are different from Goldsmith-Pinkham et al. (2020) which

[15] I control for the pre-trends and ex-ante county characteristics to help satisfy the parallel trend assumption for the difference-in-difference.

show a positive relation between sea-level rise exposure deciles and real estate prices. This divergence could be due to the nature of their measure. Specifically, the SLR exposure will affect mainly coastal counties, which plausibly have higher house prices due to the proximity to the ocean.

After the discussion on endogeneity, I present the results on weather damages. Table XII reports the difference-in-difference and matching estimates for the annual damages. In regards to the regression set up in columns (1) to (2), I find that counties that experience a loss in natural capital have greater weather damages. The coefficients are economically and statistically significant. In fact, after a PADDD event, a treated county experiences \$9 million in damages more than a similar county in the control group.

The sample of treated counties is small relative to the control group (252 versus 3002). Moreover, it is possible that selection bias due to differences between counties with protected areas might affect the results. In addition, as highlighted in the recent econometric literature, difference-in-difference estimators might be biased when heterogeneous effects are present (Callaway and Sant'Anna (2020) and Sun and Abraham (2020)).

Hence, I utilize nearest neighbor matching to clarify the results. Matching is not affected by heterogeneous effects across groups since the matching algorithm finds the most appropriate counterfactual. The matching approach is described as follows: I use nearest k-neighbor covariates matching (with replacement) with Mahalanobis distance, described in the formula below.

$$D^2 = (x - m)^T \cdot C^{-1} \cdot (x - m), \tag{3}$$

where D^2 is the square of the Mahalanobis distance, x is the vector of the observations (row in a dataset), m is the vector of mean values of independent variables (mean of each column), C^{-1} is the inverse covariance matrix of independent variables. This distance measure transforms the covariates into uncorrelated variables, scales the covariates to make their variance equal to one, and then calculates the Euclidean distance.[16]

The covariates used for the matching are the following: urban-rural classification, an Atlantic indicator, a coastal county indicator, personal income, population, density, the trend in the population ($t-2$ to $t-1$), and $Weather\,Exp._{1-5}$. I use the indicator for Atlantic and coastal because these areas are more prone to experience considerable damages from hurricanes.[17]

The results of the matching are reported in column (5). We can see that the average treatment effect on the treated (ATET) estimated using covariates matching shows that the counties that experienced natural capital loss report statistically significant higher annual damages (23.75 with z statistic of 1.71). This result is also economically significant since there is a $23 million difference in damages between the treated and the control group.

C. Municipal Bond Yields Analysis

After showing that weather-related damages increase when natural capital is lost, I study the implications of this relationship on municipalities' cost of debt. My main prediction is that municipal bond yields increase after a loss in natural capital due to the increased natural disaster risk. I test this hypothesis using two quasi-experiments. First, I study the short-term effects on municipal bonds after an extreme weather event. In this analysis, I compare the volume-weighted yields of municipal bonds issued by counties that experienced a loss in natural capital to the yields of bonds issued by counties that did not. In other words, I hypothesize that counties that experience a PADDD event are more affected by extreme weather events compared to similar counties that did not experience a loss in natural capital.

[16]For robustness, I compute the treatment effect using propensity score and caliper matching. The results are qualitatively similar to the ones reported in this paper.

[17]The Atlantic indicator variable equals one if the county is in one of the following states: Alabama, Connecticut, Delaware, Florida, Georgia, Louisiana, Maine, Maryland, Massachusetts, Mississippi, New Hampshire, New Jersey, New York, North Carolina, Pennsylvania, Rhode Island, South Carolina, Texas Vermont, Virginia, and West Virginia. The definition of Atlantic state is the same as in Jerch et al. (2020).

The sample under consideration contains counties that experienced extreme weather events. I select extreme weather events using the precipitation measure presented in section V.A. The months selected as extreme weather events are months in which a county experienced average precipitation greater than the 95^{th} percentile of the distribution of past precipitation. During these months, the counties selected faced exceptional levels of precipitation which likely disrupted regular business and destroyed property and crops.

Following is the regression model used for the estimation of the natural capital effect after an extreme weather event:

$$Yield_{b,c,t} = \sum_{t=-5}^{5} 1(Month = t) \times \gamma_t Treated + \theta_t{}' X_{b,c,t} + \delta_c + \delta_{s,t} + \epsilon_{b,c,t}, \tag{4}$$

for bond b, issued by county c, in month t. The coefficient of interest is γ_t, which represents the difference in volume-weighted yields between counties that experienced a natural capital loss event as of time $t = 0$ and those that did not. I considered a county as treated if a PADDD was enacted in its territory no earlier than three years before the weather event. The vector of controls X includes time-varying county characteristics (urban-rural classification, population, density, $Weather\,Exp._{1-5}$, personal income, unemployement rate, and trend variables ($t-2$ to $t-1$) for population, density, personal income, and unemployment rate), municipal bond characteristics (coupon rate, general obligation indicator, rating, years to maturity, and size of the bond issue), and the intensity of the weather event. The use of state-year fixed effects allows to control for time-varying local economic conditions. Moreover, the county fixed effects control for time-invariant county characteristics as discussed in section V.B. Hence, the coefficient estimates are identified from the difference in yields of bonds issued in the same state and trading in the same year.

Table XIII reports the results of the difference-in-difference analysis. The coefficients in columns (1) to (3) show that the difference between treated and control counties turns from negative to positive after the natural disaster for all months except for one (Month-3).

In fact, in the period before the event, the difference in yields is negative, possibly due to confounding features such as proximity to the coastline that promotes better economic circumstances (i.e., lower local economic risk). However, after an extreme weather event, the difference turns positive, suggesting that counties that face natural capital loss suffer more severe weather damages compared to similar non-PADDD areas.

The economic magnitude of this difference is significant since the yields change from between 0 and -10 basis points to 3 and 23. The difference between column (1) and the other two columns is that the reference month is the month before the weather event in column (1) and the month two periods before the event in columns (2) and (3). I utilize $t-2$ as a reference since some extreme weather events could be forecasted in advance and markets might reflect this forecast accordingly. I also show in Table XIV the results with regression specifications which include a triple-interaction term between the treatment, the period after the extreme weather event, and the disaster intensity ($Weather\,Exposure$). As we can see, the treatment and the intensity of the disaster are important when considering the change in the local cost of debt related to climate change risk.

The second way I test the effect on municipal bonds uses the natural capital loss event as an exogenous shock to the county's natural capital. The empirical setup is similar to equation (4) with the same vector of controls, except that the periods used are years.

$$Yield_{b,c,t} = \sum_{t=-7}^{7} 1(Year = t) \times \gamma_t Treated + \theta_t{}' X_{b,c,t} + \delta_c + \delta_{s,t} + \epsilon_{b,c,t}, \tag{5}$$

for bond b, issued by county c, in year t. The coefficient of interest is γ_t.

Table XV reports the results of the difference-in-difference estimation using PADDD as quasi-experiment. As we can see in column (3), similarly to Table XIII, the coefficients are predominantly negative for the pre-PADDD period varying from -3 to -14 basis points. On the other hand, in the post-PADDD period, the coefficients are predominantly positive between 1 and 29 basis points (Year 1 and 3 are the only exceptions with negative values).

The economic and statistical significance of the results is similar to the previously discussed monthly analysis.

Similar to the previous analysis, I report the results of the triple interaction between the treatment, the year, and the standardized disaster exposure in Table XVI. This test provides supporting evidence that both the exposure to extreme events and the destruction of nature affect the cost of debt of the municipality. The specifications are the same as equation (4) except that I add another interaction with $Weather\ Exp._t$. The results are consistent with Table XV. Lastly, I utilize the spread between the municipal bond yields and the maturity-matched municipal market AAA-rated tax-exempt benchmark curve as a robustness test for the analysis described by equation (4). The results are reported in the appendix and are qualitatively similar to the analysis reported in the paper.

The economic significance of these results is quite large. In fact, the effect of natural capital could be as high as 10.15% of the yield of an average bond (3.04%). Moreover, I can estimate the effect on the cost of debt for the county, assuming that the yield after the disaster reflects the updated risk of the county. Specifically, on an average bond issue of $19.5 million and an average maturity of 17.31 years, a county could save as much as $1,113,899 in coupon payments if they "protect" their protected areas.[18] Overall, these results highlight the short- and long-term effects of natural capital loss for local economies and the municipalities' cost of debt. In addition, the analysis informs policy-makers about the relationship between climate change risk, local cost of debt, and nature conservation.

D. Matching Analysis for Municipal Bond Yields

The results reported in this paper may be affected by selection bias. Specifically, counties that experience natural capital loss events might be different from non-PADDD counties. Moreover, unobservable bond-time factors could be correlated with the pricing of the debt

[18] $0.33\% \times \$19.5$ million $\times$ 17.31 years.

instrument and consequently result in biased estimates. However, some of the observable county characteristics do not suggest that counties that experience natural capital loss are different in some way from non-PADDD counties. Specifically, Table XI shows that there are slight differences in the characteristics reported. On the other hand, the lack of controls does not allow for meaningful comparisons for these characteristics.

To alleviate the concerns from selection bias, in addition to the fixed-effect model and difference-in-difference estimation, I estimate the effect of natural capital using matching. First, I restrict the matches to bonds issued in the same state with the same rating and the same type (general obligation or revenue). I allow a maximum of one year difference in maturity and a maximum of five months difference in the event date. Next, I utilize a propensity score to find the best counterfactual for each treated bond (those issued in a county that experienced a natural capital loss event) using the county and bond characteristics ex-ante the extreme weather event. The variables used are the following: county extreme weather exposure in the past five years, density, population, personal income, unemployment rate, natural capital size (protected area), bond coupon rate, and years to maturity.

The final sample includes only the matched control and treated observations. Specifically, the sample contains 143 unique bonds from counties that experienced a natural capital loss event and 286 (two control observations for each treated one) comparable bonds of counties that did not experience a PADDD event. The results in Table XVII are estimated using the regression:

$$y_{i,t} = \alpha + \gamma_1 Treated + \gamma_2 Post + \gamma_3 Treated \cdot Post \,, \tag{6}$$

where γ_3 is the coefficient of interest.

This approach is similar to Boulongne et al. (2020) and does not necessitate fixed effects or control variables since the sample comprises only matched treated and control observations. The results show that, after an extreme weather event, bonds in counties that experience natural capital loss report a 25 basis point increase in yields compared to bonds in counties that did not experience natural capital loss. The results are qualitatively similar to the estimates without matching. The economic magnitude of the effect is considerable. For instance, for an average bond yield, if the county were to issue new bonds for an identical project, the coupon payments would increase to as much as \$840,487.[19]

Next, I exploit the heterogeneity in the use of proceeds to study the cross-sectional effect of natural capital. Using the same sample, I estimate the following regression:

$$y_{i,t} = \alpha + \gamma_1 Treated + \gamma_2 Post + \gamma_3 Physical + \gamma_4 Treated \cdot Post \cdot Physical, \tag{7}$$

where *Physical* represents the indicator for physical use of proceeds.[20] The coefficient of interest is γ_4 which represents the differential effect on physical projects. The estimates in column (1) show that bonds issued for physical projects are more affected than the rest of the sample by 17 basis points.

Second, following Crabbe and Turner (1995), Bernstein et al. (2019) Larcker and Watts (2020), and Schwert (2020), I estimate the effect of natural capital loss using paired municipal bonds issued by the same county in the same year that differentiate only by the use of proceeds. The advantage of this approach is that it removes the impact of unobservable bond-year factors that might correlate with the instrument's risk or pricing. Eliminating this concern allows finding the more appropriate counterfactual.

For example, in April 2011, Los Angeles County, CA, issued a municipal bond to fund a project on water utilities. In July of the same year, Los Angeles County, CA, also issued a bond with "refunding" as use of proceeds.

It is clear that the difference in risk between the two instruments would be the impact of climate change risk and, specifically, mitigation risk. On the other hand, this approach

[19] 0.249% × \$19.5 million ×17.31 years.

[20] See table IX for details on the use of proceeds classification.

considerably limits the number of observations utilized for the estimation. The results in Table XVII column (2) describe similar magnitudes to the ones using matching on county characteristics.

Overall, the results provide interesting insights regarding the value of nature as it pertains to mitigating disaster risk. The difference-in-difference as well as the matching estimators suggest that the effect of nature should not be due to selection bias.

E. Spillover Effects

The effects of natural capital loss are not limited to the county that possesses the natural capital. Neighboring counties are also impacted during extreme weather events. Moreover, due to the spatial and economic link between neighboring counties, even counties not hit by an extreme weather event might be affected. In order to study this phenomenon, I adapt the empirical approach by Duflo and Saez (2003) and identify counties within a 25-mile radius from a county that experiences a PADDD event as treated counties (i.e., affected by natural capital loss) and exclude the counties that directly experienced the PADDD. The distances between counties are great-circle distances calculated using the Haversine formula based on internal points in the county.[21]

In column (1), I report the results of the regression analysis using the same empirical approach as in equation (4) with the same vector of controls. Instead, columns (2) and (3) report the results of the matching estimation. The procedure used for matching model is equal to the one described in section V.D and the only difference is the definition of treated and control group. The results in Table XVIII show that the effect is still persistent when including only neighboring counties in the model. Moreover, this suggests that the economic significance of the results is more extensive since the mitigating effects of natural capital extend to counties nearby. In addition, as shown in Table XVII, bonds issued for physical

[21] The data on county distance is available on the National Bureau of Economic Research (NBER) website (`https://www.nber.org/research/data/county-distance-database`).

projects are the most affected.

E.1. Farming-Dependendent County Analysis

The information from the U.S. Department of Agriculture allows me to classify counties by their economic dependence. Thanks to this variability in economic dependence, it is possible to analyze the heterogeneous effects of counties. Farming is one of the industries most exposed to extreme weather and water stress. In addition to the mitigating effect of extreme weather, protected areas are critical in preserving the natural water cycle and alleviate water stress.[22] For these reasons, I conjecture that counties more economically dependent on farming should be affected most. Table XIX reports the estimates of the difference-in-difference analysis using natural capital loss events as a shock. The treated group contains counties that possess the natural capital affected by PADDD as well as counties within a 25-mile radius. The outcome variables analyzed are the monthly volume-weighted municipal bond yields, the county personal income, and county population change.

The results show that natural capital loss affects farming counties more than other counties and impacts other important economic outcomes, such as population migration and personal income. More importantly, this analysis highlights that the consequences of natural capital loss are perceived in local rural counties and can affect large industries such as farming.

The effects reported could be due to the impact of extreme weather events as well as water stress. As highlighted in Strobl (2011) and Mahajan and Yang (2020), after a natural disaster, the population migrates to safer regions and this migration affects economic growth.

[22] McNeely (1994), Dudley and Stolton (2003), Ervin (2011), MacKinnon et al. (2011), Figgis et al. (2015), Harrison et al. (2016), Dudley et al. (2016), and Zhang et al. (2020) are some studies that portray the relationship between protected areas and the water cycle.

VI. Conclusion

In this study, I highlight an essential and valuable characteristic of protected areas. Nature provides one of the best technologies to fight global warming and mitigate the impact of natural disasters. Studies in the environmental and conservation literature describe the mitigation role of natural areas against extreme weather events. This study brings into economic terms this crucial role that nature covers. In fact, natural capital can decrease local climate risk and decrease the counties' cost of debt. First, I show that areas that experienced a loss in natural capital face larger weather-related damages. Next, I connect the increased exposure to weather damages to the borrowing costs of counties.

The results show that counties that destroy their natural capital experience a higher cost of debt after an extreme weather event as well as after a PADDD event reflecting the increased local climate risk. Moreover, the bonds' use of proceeds provides valuable insights regarding the cross-sectional heterogeneity in climate risk exposure. In fact, bonds issued to fund physical infrastructure projects are more sensitive to mitigation risk. The effects of natural capital loss are not only limited to the counties that possess this capital but also to their neighboring counties. The evidence shows that neighboring counties perceive the effect of natural capital loss. In addition, I present the effects of natural capital loss on population migration and personal income. I find that areas affected by natural capital loss report higher population migration, possibly due to the increased impact of weather events. Lastly, exploiting the cross-sectional heterogeneity in county economic dependence, I show that natural capital loss affects farming counties the most due to their exposure to extreme weather and reliance on water. This latter results highlight the macroeconomic consequences of natural capital loss as it pertains to food production.

On the other hand, this study might provide only a lower bound of the effect of protected areas since I am studying a subset of protected areas that have been affected by downsizing, downgrading, or degazettement. However, the use of these natural capital loss events provides substantial evidence for identifying causality since it provides a shock to the local natural capital. The finance and economic literature has explored the consequences of natural disasters on local and national economies; however, this study is the first to economically value the mitigating power of local natural capital against extreme weather events. The study provides valuable insights for policymakers in favor of nature conservation and raises awareness with respect to one of the innumerable qualities of nature.

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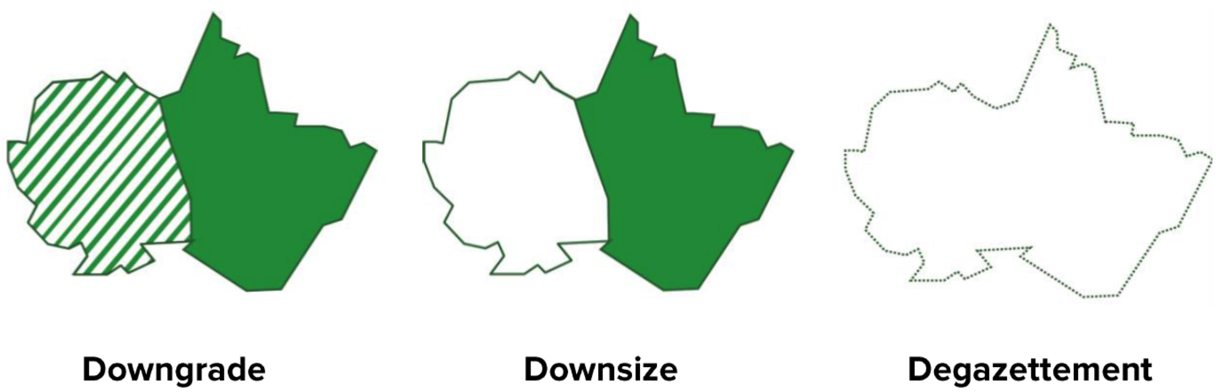

Figure 1: This figure represents the graphical representation of protected area downgrading, downsizing, and degazettement (PADDD) (Mascia et al. (2012)).

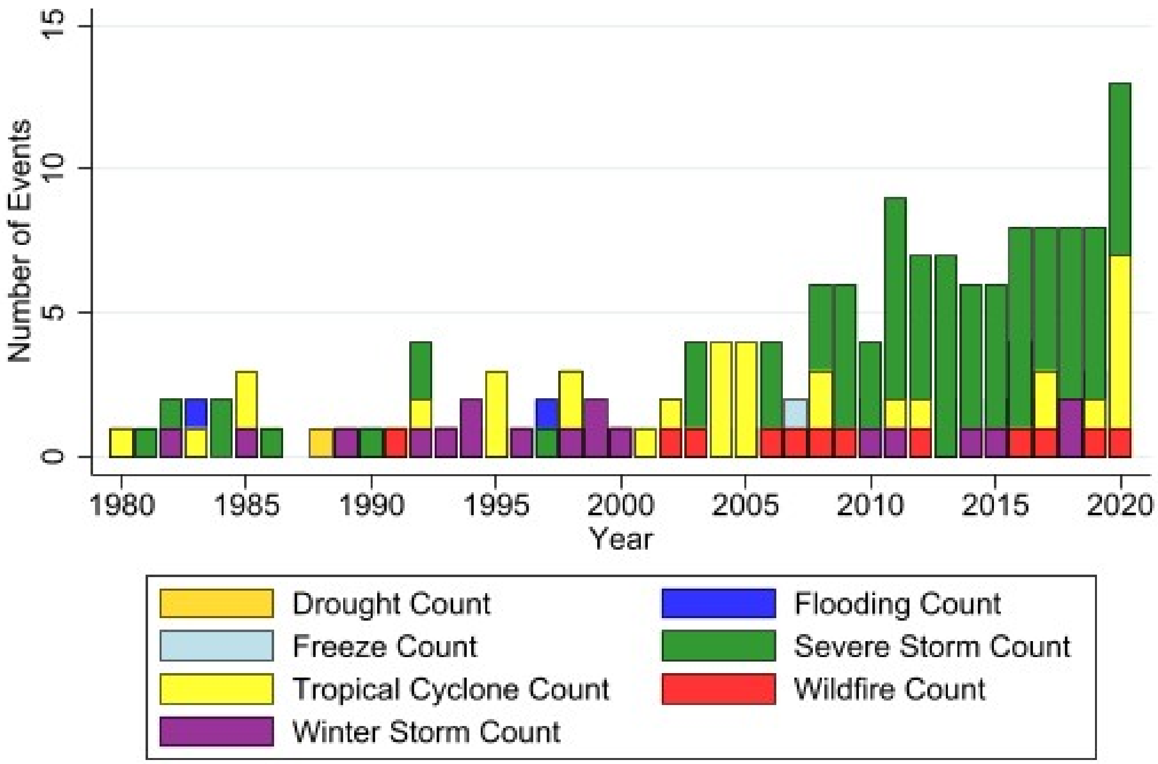

Figure 2: This graph reports the frequency of billion-dollar disaster events in the United States from 1980 to 2020 by type of disaster. The data was collected from the NOAA website.

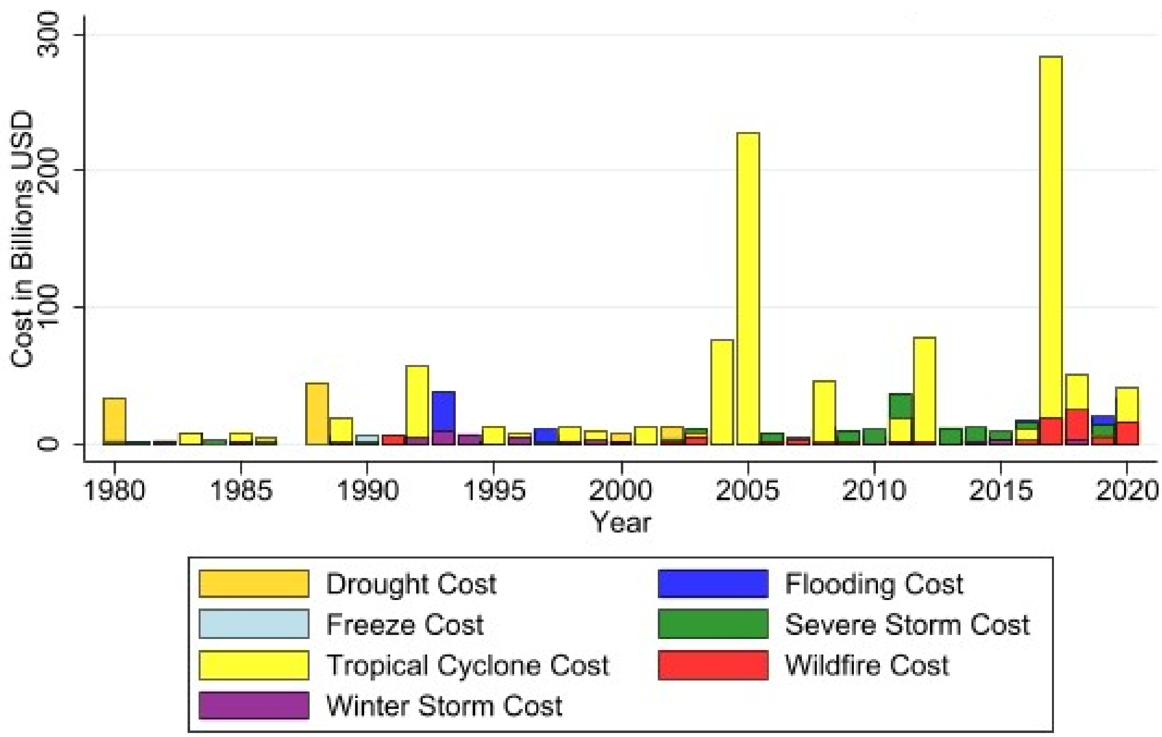

Figure 3: This graph reports the CPI-adjusted damages of billion-dollar disaster events in the United States from 1980 to 2020 by type of disaster. The data was collected from the NOAA website.

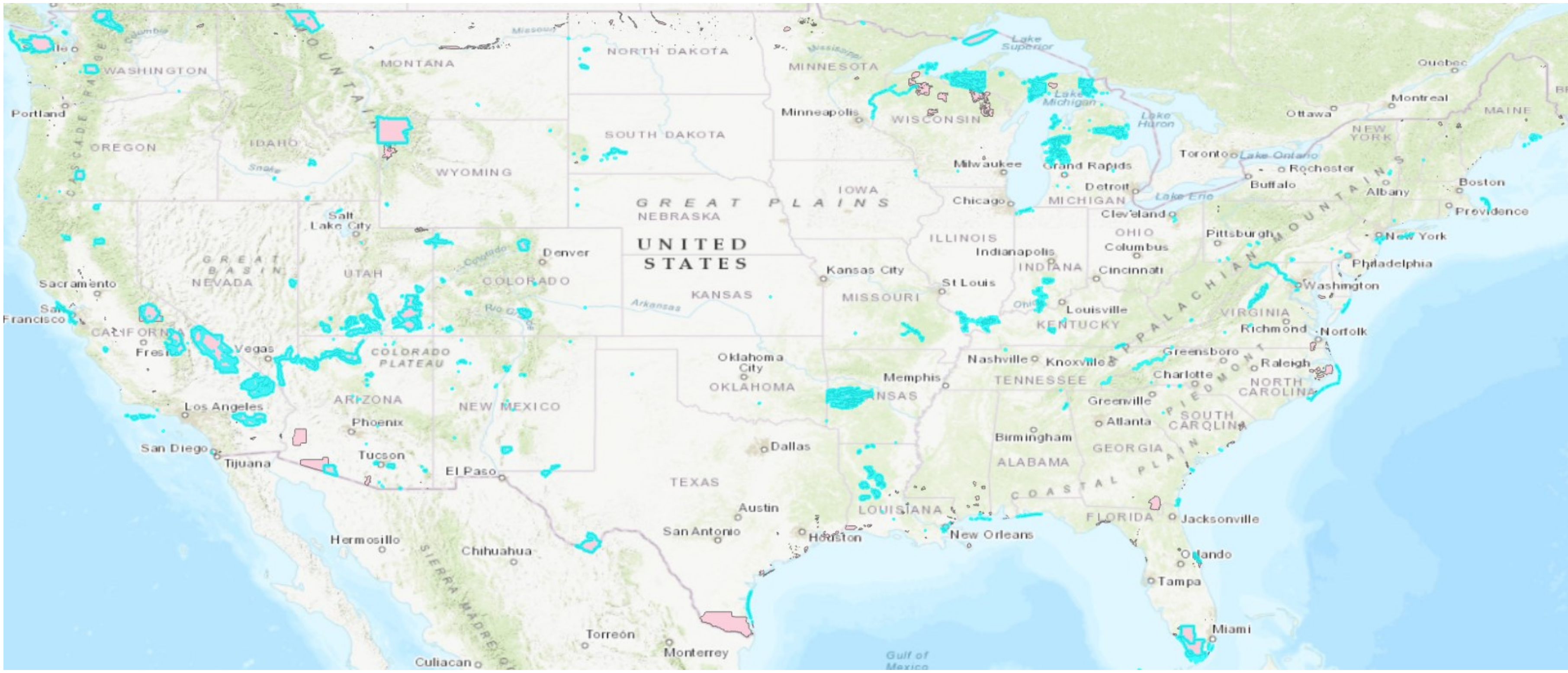

Figure 4: This figure represents the protected areas in the contiguous U.S. that experienced a PADDD event from 1976 to 2018.

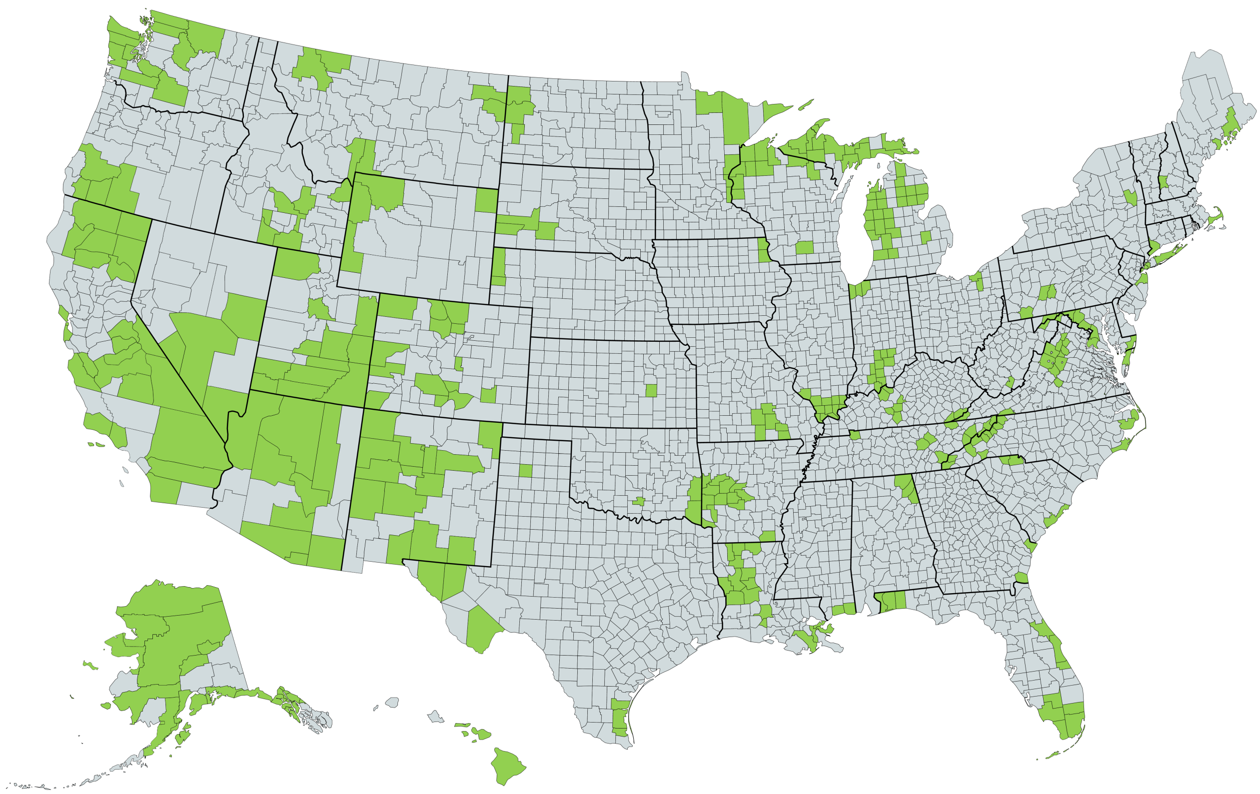

Figure 5: This figure represents the U.S. counties that experienced natural capital loss (i.e. PADDD) from 1976 to 2018.

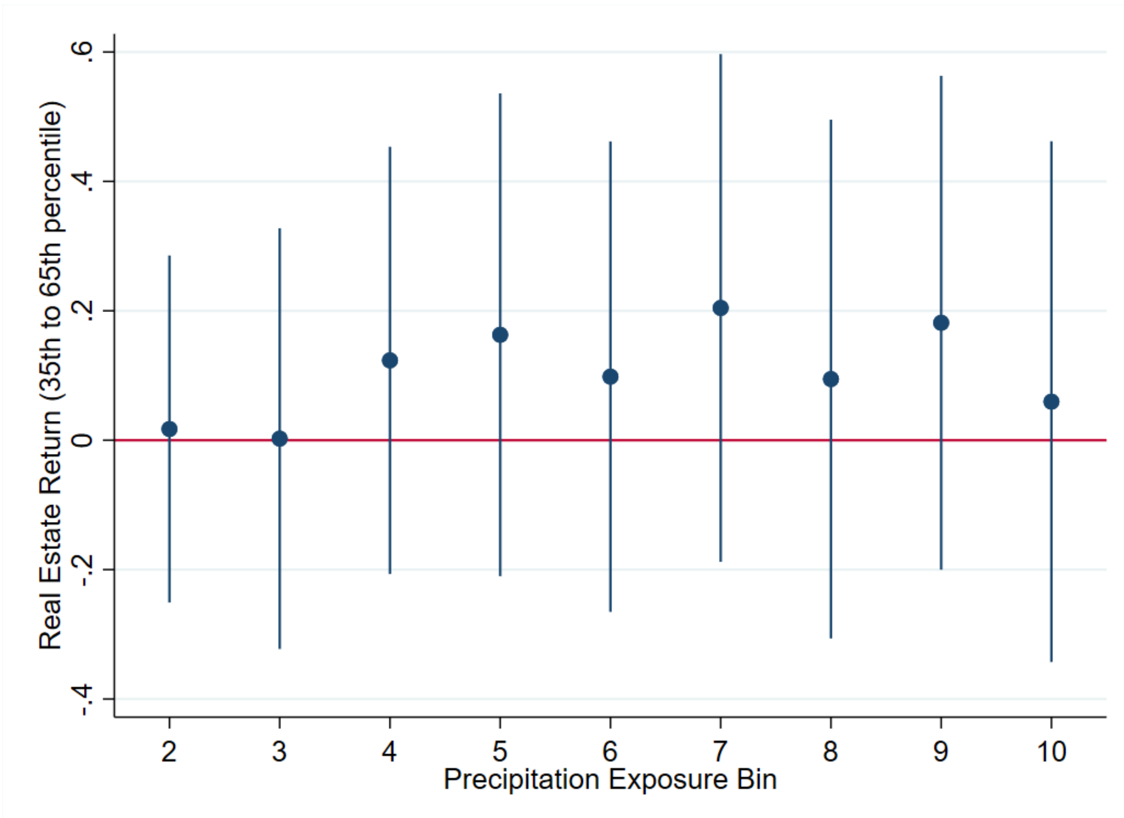

Figure 6: This figure represents coefficients from the semi-parametric regressions of real estate returns on precipitation exposure. The real estate return is calculated using the Zillow All Homes Time Series, Smoothed and Seasonally Adjusted for homes in the 35^{th} and 65^{th} percentile. Each county is sorted into a specific bin using the standardized annual precipitation exposure (equation (1)). The coefficients are estimated relative to counties in the first bin (lowest precipitation exposure). The controls include urban-rural classification (indicator), personal income, population, and density. The regression specification includes county and state-year fixed effects and the standard errors are clustered at the state level.

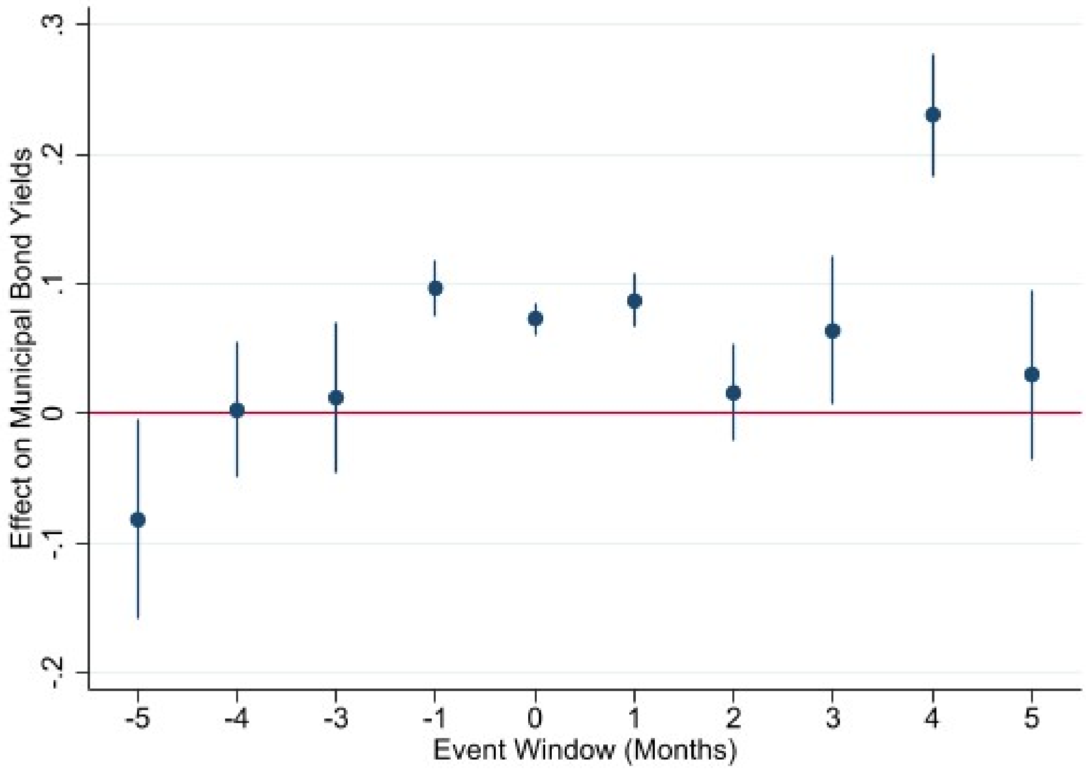

Figure 7: This figure represents the coefficients from the difference-in-difference regression of monthly municipal bond yields before and after an extreme weather event (Table XIII column (2)). The coefficients are estimated using month $t-2$ as reference. The regression includes county and state-year fixed effects as well as the following controls: urban-rural classification (indicator), personal income, population, density, $Weather\ Exp._{1-5}$, coupon rate, bond rating, years to maturity, and size of the bond issue.

Table I: Weather Damages by State

This table reports the summary statistics for the annual damages from weather events for each state in the contiguous United States. This information is collected from the NOAA and the sample period starts in 1969 and ends in 2020. The annual damages reported are in $ millions and are CPI-adjusted to 2019 U.S. dollars.

Panel A: Summary Statistics for Damages					
Annual Damages	N	Mean	S.D.	Min	Max
County	153,270	4.97	128.05	0	27,619.17
State	2,450	311.22	2,198.13	0	67,871.12

Panel B: Annual State Damages					
State	Mean	S.D.	State	Mean	S.D.
TX	2,269.14	5,322.83	MI	138.15	300.40
FL	2,205.62	7,277.34	KY	131.47	187.57
LA	1,795.52	9,644.15	WA	125.44	306.52
MS	881.50	4,782.19	SC	115.05	233.38
GA	846.12	2,646.36	NM	97.62	337.56
NJ	646.96	3,981.01	AZ	97.54	464.42
CA	579.86	1,057.78	NV	85.86	361.51
IA	523.81	937.69	OR	85.68	239.65
OK	432.21	729.92	VA	83.84	166.05
NC	427.52	1,134.22	ID	57.56	190.31
AL	413.71	953.22	CT	56.12	175.88
IL	256.46	426.59	MD	39.73	107.10
MO	255.46	572.71	WV	35.13	64.18
OH	254.96	439.10	MT	34.01	143.68
NE	234.15	300.77	SD	29.87	40.38
AR	221.32	421.63	ME	26.67	104.28
CO	201.98	426.29	NH	26.63	142.24
KS	199.62	280.05	UT	26.12	71.42
IN	197.92	725.04	VT	25.11	139.19
PA	196.01	481.14	MA	23.42	58.72
TN	187.49	507.36	WY	8.47	17.50
MN	174.98	377.04	DE	4.66	12.93
ND	172.92	831.84	RI	3.17	14.60
NY	165.50	303.80	DC	1.80	6.93
WI	149.71	237.66			

Table II: PADDD Summary Statistics by Year

This table reports descriptive statistics by year for the PADDD events in the United States, excluding Alaska and Hawaii. This information is collected from the WWF (Conservation International and World Wildlife Fund (2019)). The sample period starts in 1976 and ends in 2017.

Year	Counties Affected	Percent	Area Affected (km^2)	Area Affected (mi^2)
1976	1	0.23	1.49	0.58
1978	1	0.23	39.85	15.38
1980	4	0.92	3,204.97	1,237.45
1986	102	23.56	8,445.09	3,260.67
1987	3	0.69	369.53	142.68
1988	5	1.15	1,139.72	440.05
2000	4	0.92	5,229.45	2,019.10
2005	5	1.15	29.36	11.34
2007	4	0.92	1,139.20	439.85
2011	40	9.24	5,683.69	2,194.48
2012	25	5.77	4,454.74	1,719.98
2016	235	54.27	31,858.90	12,300.79
2017	4	0.92	3,388.29	1,308.23
Total	433			

Table III: PADDD Summary Statistics by Urban-Rural Classification - 1976-2017 Subsample

This table reports descriptive statistics by urban-rural classification for the PADDD events in the United States, excluding Alaska and Hawaii. The information about the PADDD is collected from the WWF (Conservation International and World Wildlife Fund (2019)). The data for the urban-rural classification are collected from the Economic Research Service of the U.S. Department of Agriculture. The sample period starts in 1976 and ends in 2017. The % of Total Area Affected is calculated by dividing the protected area in the specific county by the county's total land area.

Urban-Rural Classification	Freq.	Percent	Area Affected (km^2)	Area Affected (mi^2)	% of Total Area Affected
Large Central Metro	16	3.70	3,339.62	1,289	5.1%
Fringe Metro	26	6.00	3,589.44	1,386	5.5%
Medium Metro	65	15.01	6,936.47	2,678	10.7%
Small Metro	46	10.62	5,722.63	2,210	8.8%
Micropolitan	88	20.32	10,182.37	3,931	15.7%
Non-core	192	44.34	35,213.75	13,596	54.2%
Total	433	100	211,987.28	81,848	

Table IV: PADDD Summary Statistics by Urban-Rural Classification - 2005-2017 Subsample

This table reports descriptive statistics by urban-rural classification for the PADDD events in the United States, excluding Alaska and Hawaii. The information about the PADDD is collected from the WWF (Conservation International and World Wildlife Fund (2019)). The data for the urban-rural classification are collected from the National Center for Health Statistics (NCHS). The sample period starts in 2005 and ends in 2017. The % of Total Area Affected is calculated by dividing the protected area in the specific county by the county's total land area.

Urban-Rural Classification	Freq.	Percent	Area Affected (km^2)	Area Affected (mi^2)	% of Total Area Affected
Large Central Metro	12	3.83	2,842	1,097	6.10%
Fringe Metro	26	8.31	3,589	1,386	7.71%
Medium Metro	54	17.25	6,154	2,376	13.22%
Small Metro	39	12.46	4,564	1,762	9.80%
Micropolitan	68	21.73	8,312	3,209	17.85%
Non-core	114	36.42	21,092	8,144	45.31%
Total	313	100	46,554	17,975	

Table V: Number of PADDD Events by State - 1976-2017 Subsample

This table reports the number of PADDD events by state, excluding Alaska and Hawaii. This information is collected from the WWF (Conservation International and World Wildlife Fund (2019)). The sample period starts in 1976 and ends in 2017.

State	Freq.	State	Freq.
MI	44	MO	6
AR	42	MT	6
CA	31	NY	5
FL	24	MS	4
IL	24	OR	4
WA	20	SD	4
LA	16	WY	4
NM	15	AL	3
UT	15	ND	3
CO	14	PA	3
VA	14	SC	3
WI	14	WV	3
IN	13	GA	2
NC	13	IA	2
AZ	10	MA	2
TN	10	ME	2
KY	8	NE	2
NV	8	OH	2
MD	7	CT	1
MN	7	KS	1
OK	7	NH	1
TX	7	NJ	1
ID	6		
Total	433		

Table VI: Number of PADDD Events by State - 2005-2017 Subsample
This table reports the number of PADDD events by state, excluding Alaska and Hawaii. This information is collected from the WWF (Conservation International and World Wildlife Fund (2019)). The sample period starts in 2005 and ends in 2017.

State	Freq.	State	Freq.
AR	28	NV	4
CA	27	OK	4
FL	19	OR	4
WA	17	SD	4
NM	15	TN	4
UT	15	WY	4
CO	14	AL	3
VA	13	IN	3
IL	12	ND	3
WI	12	PA	3
AZ	10	SC	3
MI	10	WV	3
MD	7	GA	2
MN	7	IA	2
TX	7	ME	2
ID	6	NE	2
KY	6	OH	2
LA	6	CT	1
MO	6	KS	1
MT	6	MA	1
NY	5	NH	1
MS	4	NJ	1
NC	4		
Total	313		

Table VII: Definitions of the PADDD Causes

This table reports the definition of the causes of PADDD as reported in the WWF database (Conservation International and World Wildlife Fund (2019)) and Mascia et al. (2012).

Cause of PADDD	Definition
Infrastructure	PADDD resulting from the legal authorization of previously prohibited structures that form the system of public works of a country, state, or region. Includes dams, roads, railways, pipes, electrical grid, power-generation facilities, telecommunications towers, transportation facilities, hospitals, schools, sports facilities, etc. Does not include churches and other religious institutions; tourism facilities.
Land Claims	PADDD resulting from legal restoration of full or partial rights to indigenous peoples or other local residents previously displaced or divested of de jure or de facto rights as a result of protected area establishment or management. Includes rights of access, withdrawal, management, exclusion, and alienation (Schlager & Ostrom, 1992; Mascia & Claus 2009). Does not include excision of human settlements from protected areas.
Mining	PADDD resulting from the legal authorization of previously prohibited industrial or semi-industrial scale mining operations. Includes open-pit mines, underground mines, riverbed mines, quarrying, subsurface mines, and related activities for the extraction of metals, minerals, coal, rock, stone, sand, and other non-renewable resources, excluding oil and gas. Does not include coal-seam gas (see "Oil and Gas"); peat harvesting (see "Subsistence" or "Other" depending on scale of operation) or artisanal mining (see "Subsistence").
Oil and Gas	PADDD resulting from the legal authorization of previously prohibited industrial or semi-industrial scale operations for exploration or extraction of fossil fuels other than coal. Includes all surveying and exploration, onshore and offshore drilling, and related activities. Does not include oil and gas refineries and other petrochemical operations (See "Industrialization"); gas pipelines (see "Infrastructure").
Subsistence	PADDD resulting from the legal authorization of previously prohibited non-commercial or small-scale commercial, artisanal, or non-industrial (non-mechanized) extraction or production activities. These activities are often (but not always) local or personal consumption. Includes small holder farming and grazing, non-timber forest product harvesting, fuel wood harvesting, hunting, fishing, artisanal mining, and related activities.
Other	Any proximate cause of downgrading, downsizing, or degazettement that cannot be classified in any other cause category.
Unknown	Proximate cause of PADDD is not known.

Table VIII: PADDD Summary Statistics by Cause

This table reports descriptive statistics by cause for the PADDD events in the United States, excluding Alaska and Hawaii. The information about the PADDD is collected from the WWF (Conservation International and World Wildlife Fund (2019)). The sample period starts in 1976 and ends in 2017. The % of Total Area Affected is calculated by dividing the PA in the specific county by the county's total land area. The definitions of PADDD causes are listed in Table VII.

Cause of PADDD	Freq.	Percent	Area Affected (km^2)	Area Affected (mi^2)	% of Total Area Affected
Infrastructure	144	33.3%	13,827	5,339	21.3%
Land Claims	24	5.5%	8,909	3,440	13.7%
Mining	8	1.8%	6,593	2,546	10.1%
Oil and Gas	10	2.3%	1,169	451	1.8%
Other	8	1.8%	2,218	856	3.4%
Subsistence	235	54.3%	31,859	12,301	49.0%
Unknown	4	0.9%	409	158	0.6%
Total	433	100%	64,984	25,091	100%

Table IX: Bonds' Use of Proceeds Classification - Physical vs Non-Physical
This table reports the words used to classify bonds into "physical" and "non-physical" according to their respective use of proceeds.

Use of Proceeds	
Physical	Non-Physical
Electricity, Power	Student Loans
Natural Gas	Resource Recovery
School	Miscellaneous
Recreational	Economic Defeasance
Water, Sewer	Cash Flow Management
Bridge	Lawsuit, Settlement
Highway, Parking	Pension
Correctional Facility	Swap Termination
Hospital, Nursing Home, Retiremente Home	Jobs Training
Housing	Economic IMP
Telecommunications	Industrial
Airport	Refunding
Marina, Port	Repayment of Bank Loan
University, College	Property Acquisition

Table X: Category Definitions for PAD-US

This table reports the definition of the protected area categories listed in the PAD-US collected by the United States Geological Survey (USGS).

Category	Description	Example
Fee	Land owned outright by public agencies, nonprofits, or private entities.	National Forest lands owned by the U.S. Forest Service.
Easement	Non-sensitive conservation and open space easements provided by the National Conservation Easement Database (NCED).	Privately owned land with a voluntary conservation easement agreement in place.
Designation	Policy-designated areas that may overlap fee owned land, easements, or other designations.	Legislatively designated Wilderness Areas overlapping federally owned BLM, USFS, FWS, or NPS lands.
Proclamation	Congressionally designated proclamation, Tribal areas, military lands, and other boundaries providing context for planning or references purposes. Does not represent ownership boundaries.	National Park or National Forest boundaries congress approved for voluntary land acquisition within (boundary does not represent private, state, or locally owned/managed land in holdings).
Marine	Protected waters, including federal, state, and local areas in the National Oceanic and Atmospheric Administration (NOAA) MPA inventory, as well as Bureau of Ocean Energy Management (BOEM) off shore areas managed for energy and minerals.	National Estuarine Research Reserves

Table XI: Summary Statistics
This table reports summary statistics of the variables used in the paper for two groups of observations: counties that experienced a PADDD event and those that did not.

	PADDD			No PADDD		
	Obs.	Mean	St.Dev.	Obs.	Mean	St. Dev.
Personal Income	8,650	19,561	14,721	126,321	19,138	12,875
Weather Damages	8,650	2.59	37.15	126,321	3.01	64.05
Weather Exp.	8,650	0.11	1.01	126,321	0.36	0.85
Population	8,650	60,521	109,514	126,321	44,985	81,882
Density	8,650	43.19	65.39	126,321	69.79	127.77
Urban-Rural Classification	8,650	5.25	1.00	126,321	5.30	1.04
Protected Area	8,650	18.32%	15.62%	126,321	3.28%	5.85%
Population Trend	8,304	1.13%	2.47%	121,211	0.52%	2.03%
Density Trend	8,304	1.13%	2.47%	121,211	0.52%	2.03%
Mun. Bond Yield	21,244	3.04	1.17	714,775	3.02	1.10
Years to Maturity	21,244	17.71	7.73	714,775	15.43	7.07
Bond Age	21,244	1.91	2.83	714,775	1.81	2.69
Housing Price Index (35^{th} to 75^{th})	2,767	221,474	166,856	51,791	145,764	113,227

Table XII: Difference-in-Difference and Matching Estimation of Annual Damages

This table reports the difference-in-difference and matching estimation coefficients with annual damages as dependent variable and PADDD as exogenous shock. The Treated variable indicates if the county experienced a PADDD event. The controls include urban-rural classification (indicator), personal income, unemployment rate, population, density, $Weather\,Exp._{1-5}$, $Weather\,Exp._{6-10}$ and trend variables ($t-2$ to $t-1$) for population, density, personal income, and unemployment rate. The specifications include county and state-year fixed effects. The standard errors are clustered at the state level. The covariates matching is performed using Mahalanobis distance. The covariates utilized for the estimation are the following: urban-rural classification, Atlantic indicator, coastal county (1 if a county is on the coast), personal income, unemployment rate, population, density, trend in population ($t-2$ to $t-1$), and $Weather\,Exp._{1-5}$. t-statistics (z-statistic for matching) are reported in parenthesis. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Annual Damages (CPI Adjusted)			
	DiD		Matching (ATET)
	(1)	(2)	(3)
Treated × Post	9.71**	9.41**	23.75**
	(1.85)	(1.83)	(1.71)
$Weather\,Exp._{1-5}$	0.41	0.71	
	(0.20)	(0.37)	
$Weather\,Exp._{6-10}$		2.20	
		(1.41)	
Controls	Y	Y	
County FE	Y	Y	
State-Year FE	Y	Y	
Observations	124,820	124,820	7,293

Table XIII. Difference-in-Difference Estimation of Municipal Bond Yields - Extreme Weather Event

This table reports the difference-in-difference estimation coefficients with monthly volume-weighted municipal bond yields as dependent variable and extreme weather events as exogenous shock. The Treated variable indicates municipal bonds of counties that experienced a PADDD event no earlier than three years before the disaster. The controls include urban-rural classification (indicator), personal income, unemployment rate, population, density, $Weather\,Exp._{1-5}$, coupon rate, bond rating, years to maturity, size of the bond issue, general obligation indicator, and trend variables ($t-2$ to $t-1$) for population, density, personal income, and unemployment rate. The specifications include county and state-year fixed effects. The standard errors are clustered at the state level. t-statistics are reported in parenthesis. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

	(1)	(2)	(3)
Treated × 1(Month −5)	−0.062	−0.054	−0.082***
	(−0.72)	(−0.62)	(−2.06)
Treated × 1(Month −4)	−0.107	−0.091	0.003
	(−1.86)	(−1.56)	(0.11)
Treated × 1(Month −3)	−0.005	0.013	0.012
	(−0.07)	(0.20)	(0.42)
Treated × 1(Month −2)	−0.019	-	-
	(−0.31)	-	-
Treated × 1(Month −1)	-	0.088***	0.098***
	-	(3.62)	(3.68)
Treated × 1(Month 0)	0.041***	0.059***	0.073***
	(3.00)	(4.07)	(4.14)
Treated × 1(Month 1)	0.059***	0.081***	0.087***
	(2.62)	(3.49)	(8.25)
Treated × 1(Month 2)	0.053	0.073	0.016
	(1.27)	(1.73)	(0.84)
Treated × 1(Month 3)	0.05	0.068	0.064*
	(0.78)	(1.07)	(2.20)
Treated × 1(Month 4)	0.230***	0.247***	0.230***
	(4.38)	(4.69)	(4.58)
Treated × 1(Month 5)	0.032	0.041	0.030
	(0.44)	(0.57)	(0.89)
Controls	Y	Y	Y
Personal Income	Y	N	Y
County FE	Y	Y	Y
State-Year FE	Y	Y	Y
Observations	205,105	257,761	205,105

Table XIV. Difference-in-Difference Estimation of Municipal Bond Yields - Extreme Weather Event - Triple Interaction

This table reports the difference-in-difference estimation coefficients with monthly volume-weighted municipal bond yields as dependent variable and extreme weather events as exogenous shock. The Treated variable indicates municipal bonds of counties that experienced a PADDD event no earlier than three years before the disaster. $Weather\,Exp.$ represents the intensity of the extreme weather event. The controls include urban-rural classification (indicator), personal income, unemployment rate, population, density, and $Weather\,Exp._{1-5}$, coupon rate, bond rating, years to maturity, size of the bond issue, general obligation indicator, and trend variables ($t-2$ to $t-1$) for population, density, personal income, and unemployment rate. The specifications include county and state-year fixed effects. The standard errors are clustered at the state level. t-statistics are reported in parenthesis. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

	(1)	(2)
Treated × $Weather\,Exp.$ × Post	0.137***	0.102***
	(3.08)	(2.63)
Controls	Y	Y
Personal Income	N	Y
County FE	Y	Y
State-Year FE	Y	Y
Observations	257,761	205,105

Table XV: Difference-in-Difference Estimation of Municipal Bond Yields - PADDD Event Study

This table reports the difference-in-difference estimation coefficients with annual volume-weighted municipal bond yields as dependent variable and PADDD as exogenous shock. The Treated variable indicates municipal bonds of counties that experienced a PADDD event. The controls include urban-rural classification (indicator), personal income, unemployment rate, population, density, $Weather\,Exp._{1-5}$, coupon rate, bond rating, years to maturity, size of the bond issue, general obligation indicator, and trend variables ($t-2$ to $t-1$) for population, density, personal income, and unemployment rate. The specifications include county and state-year fixed effects. The standard errors are clustered at the state level. t-statistics are reported in parenthesis. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

	(1)	(2)	(3)
Treated × 1(Year −7)	−0.057***	−0.036***	−0.053***
	(−6.19)	(−3.80)	(−5.75)
Treated × 1(Year −6)	−0.082***	−0.062***	−0.081***
	(−3.08)	(−3.74)	(−3.88)
Treated × 1(Year −5)	−0.121***	−0.103***	−0.124***
	(−3.24)	(−3.05)	(−3.29)
Treated × 1(Year −4)	−0.137***	−0.119***	−0.140***
	(−5.20)	(−4.91)	(−5.26)
Treated × 1(Year −3)	−0.109***	−0.091***	−0.110***
	(−4.96)	(−4.79)	(−3.91)
Treated × 1(Year −1)	0.050	0.021*	0.016
	(1.64)	(2.21)	(0.40)

Table XV: Difference-in-Difference Estimation of Municipal Bond Yields - PADDD Event Study - Continued

	(1)	(2)	(3)
Treated × 1(Year 0)	0.050	0.002	0.015
	(1.64)	(0.269)	(0.37)
Treated × 1(Year 1)	0.026	−0.023**	−0.010
	(0.86)	(−2.61)	(−0.25)
Treated × 1(Year 2)	0.066*	0.085***	0.099**
	(2.18)	(5.20)	(2.36)
Treated × 1(Year 3)	0.024	−0.020	−0.003
	(0.76)	(−1.30)	(−0.08)
Treated × 1(Year 4)	0.053	0.005	0.007
	(1.68)	(0.22)	(0.16)
Treated × 1(Year 5)	0.174***	0.275***	0.293***
	(5.01)	(8.73)	(6.07)
Treated × 1(Year 6)	0.289***	0.256***	0.274***
	(7.22)	(8.03)	(5.67)
Treated × 1(Year 7)	0.141***	0.108**	0.125**
	(3.38)	(3.16)	(2.51)
Controls	Y	Y	Y
Population	N	Y	Y
Density	N	Y	Y
Personal Income	N	N	Y
Bond Characteristics	Y	Y	Y
County FE	Y	Y	Y
State-Year FE	Y	Y	Y
Observations	160,238	160,238	109,010

Table XVI: Difference-in-Difference Estimation of Municipal Bond Yields - PADDD Event - Triple Interaction

This table reports the difference-in-difference estimation coefficients with monthly volume-weighted municipal bond yields as dependent variable and PADDD as exogenous shock. The main independent variables are the triple interactions between Treated, $Weather\,Exp._{1-5}$, and the relative year. The Treated variable indicates municipal bonds of counties that experienced a PADDD event. The controls include urban-rural classification (indicator), personal income, unemployment rate, population, density, and coupon rate, bond rating, years to maturity, size of the bond issue, and trend variables ($t-2$ to $t-1$) for population, density, personal income, general obligation indicator, and unemployment rate. The specifications include county and state-year fixed effects. The standard errors are clustered at the state level. t-statistics are reported in parenthesis. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

	(1)	(2)	(3)
Treated × $Weather\,Exp.$ × 1(Year −7)	−0.0336	−0.039	−0.043*
	(−1.15)	(−1.36)	(−1.75)
Treated × $Weather\,Exp.$ × 1(Year −6)	−0.0538	−0.059	−0.064*
	(−1.34)	(−1.50)	(−1.76)
Treated × $Weather\,Exp.$ × 1(Year −5)	−0.0601	−0.066	−0.070*
	(−1.43)	(−1.58)	(−1.81)
Treated × $Weather\,Exp.$ × 1(Year −4)	−0.0536	−0.059**	−0.063**
	(−1.76)	(−2.01)	(−2.38)
Treated × $Weather\,Exp.$ × 1(Year −3)	−0.0264	−0.033	−0.036
	(−0.53)	(−0.66)	(−0.78)
Treated × $Weather\,Exp.$ × 1(Year −1)	0.040	0.041	0.046
	(0.78)	(0.76)	(0.99)

Table XVI: Difference-in-Difference Estimation of Municipal Bond Yields - PADDD Event - Triple Interaction - Continued

	(1)	(2)	(3)
Treated × $Weather\,Exp.$ × 1(Year 0)	0.052***	0.053	0.057
	(9.51)	(1.23)	(1.49)
Treated × $Weather\,Exp.$ × 1(Year 1)	0.027***	0.027	0.028
	(7.84)	(1.18)	(1.40)
Treated × $Weather\,Exp.$ × 1(Year 2)	0.036***	0.035	0.217***
	(5.61)	(1.54)	(4.21)
Treated × $Weather\,Exp.$ × 1(Year 3)	0.219***	0.222*	0.251*
	(8.77)	(1.76)	(1.92)
Treated × $Weather\,Exp.$ × 1(Year 4)	0.037***	0.039	0.052
	(3.89)	(0.83)	(1.15)
Treated × $Weather\,Exp.$ × 1(Year 5)	0.014***	0.015	0.019
	(3.69)	(0.79)	(1.06)
Treated × $Weather\,Exp.$ × 1(Year 6)	0.064***	0.063	0.287***
	(2.62)	(0.54)	(14.32)
Treated × $Weather\,Exp.$ × 1(Year 7)	0.179***	0.178***	0.204***
	(4.33)	(3.88)	(4.37)
Controls	Y	Y	Y
Population	N	Y	Y
Density	N	Y	Y
Personal Income	N	N	Y
Bond Characteristics	Y	Y	Y
County FE	Y	Y	Y
State-Year FE	Y	Y	Y
Observations	160,238	160,238	109,010

Table XVII: Matching Estimation of Municipal Bond Yields - Pre/Post Extreme Weather Event

This table reports the coefficients of the matching estimation. The dependent variable is the monthly volume-weighted municipal bond yield. The Treated variable indicates municipal bonds of counties that experienced a PADDD event. Post is an indicator equal to one for observations occurring after the extreme weather event and zero otherwise. The matches are restricted to bonds issued in the same state with the same rating and with the same type (general obligation or revenue). I also allow a maximum of one year difference in maturity and a maximum of five months difference in the event date. The variables used for the propensity score include personal income, unemployment rate, population, density, $Weather\,Exp._{1-5}$, natural capital size (protected area), coupon rate, and years to maturity. The standard errors are clustered at the bond level. t-statistics are reported in parenthesis. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

	(1)	(2)
Treated × Post	0.249***	0.221***
	(3.28)	(3.29)
Treated × Post × Physical	0.166***	0.215***
	(3.40)	(2.12)
Treated Bonds	143	94
Control Bonds	286	188
Physical Bonds	202	133
Non-Physical Bonds	227	149
County Controls	Y	N
Bond Controls	Y	Y
Same County, same Year	N	Y
Observations	20,322	9,835

Table XVIII: Difference-in-Difference and Matching Estimation of Municipal Bond Yields - Pre/Post Extreme Weather Event - Neighboring Counties Only
This table reports the coefficients of the regression (column (1)) and the matching estimation (columns (1) and (2)). The sample of treated counties includes counties in a 25-miles radius from a county that experienced a natural capital loss event. The dependent variable is the monthly volume-weighted municipal bond yield. The Treated variable indicates municipal bonds of counties that experienced a PADDD event no earlier than three years before the disaster. Post is an indicator equal to one for observations occurring after the extreme weather event and zero otherwise. The control utilized for the regression estimation in column (1) include urban-rural classification (indicator), personal income, unemployment rate, population, density, and coupon rate, bond rating, years to maturity, size of the bond issue, general obligation indicator, and trend variables ($t-2$ to $t-1$) for population, density, personal income, and unemployment rate. For columns (2) and (3), the matches are restricted to bonds issued in the same state with the same rating and with the same type (general obligation or revenue). I also allow a maximum of one year difference in maturity and a maximum of five months difference in the event date. The variables used for the propensity score include personal income, unemployment rate, population, density, $Weather\,Exp._{1-5}$, natural capital size (protected area), coupon rate, and years to maturity. The standard errors are clustered at the state level for column (1) and at the bond level for columns (2) and (3). t-statistics are reported in parenthesis. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

	(1)	(2)	(3)
Treated × Post	0.132*	0.139***	0.137***
	(1.91)	(3.22)	(3.13)
Treated × Post × Physical	0.156***	0.45***	0.49***
	(2.81)	(5.38)	(5.94)
Treated Bonds	-	110	38
Control Bonds	-	220	76
Physical Bonds	-	155	63
Non-Physical Bonds	-	175	51
County Controls	Y	Y	N
Bond Controls	Y	Y	Y
Same County, Same year	N	N	Y
Fixed Effects	Y	-	-
Observations	207,921	45,436	10,384

Table XIX: Estimation of Natural Capital Loss Effect on Farming Counties

This table reports the difference-in-difference estimation coefficients with monthly volume-weighted municipal bond yields, personal income, and population as dependent variables and PADDD as exogenous shock. The sample of treated counties includes counties in a 25-miles radius from a county that experienced a natural capital loss event and the counties that contain the protected area affected by PADDD. The main independent variables are the triple interactions between Treated, Post, and the farming indicator. The Treated variable indicates counties that experienced a PADDD event. The farming indicator equals one if the county is classified as economically dependent on farming by the BEA. The controls include urban-rural classification (indicator), personal income, unemployment rate, population, density, coupon rate, bond rating, years to maturity, size of the bond issue, general obligation indicator, and trend variables ($t-2$ to $t-1$) for population, density, personal income, and unemployment rate. Columns (2) and (3) do not include bond controls. The specifications include county and state-year fixed effects. The standard errors are clustered at the state level. t-statistics are reported in parenthesis. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

	(1)	(2)	(3)
Treated × Post	0.031***	−0.045	−0.012*
	(3.41)	(−0.61)	(−1.78)
Treated × Post × Farming	0.096***	−0.346**	−0.14
	(4.21)	(−2.63)	(−1.38)
County Controls	Y	Y	Y
Bond Controls	Y	-	-
Fixed Effects	Y	Y	Y
Observations	559,144	170,293	170,293

Appendix

Nature as a Defense from Disasters:

Natural Capital and Municipal Bond Yields

I. Why do PADDD Happen?

In this section, I shed light on the causes of PADDD. As mentioned in the paper, at this time, the political and legal procedure by which PADDD are proposed and passed is not clear. To better understand if some observable county characteristics make a county more likely to experience natural capital loss, I utilize a logit model to estimate the likelihood that a PADDD happens. Specifically, I try to predict a natural capital loss event using the following county characteristics: personal income, unemployment rate, population (log), population change, density, density change, weather damages (log), extreme weather exposure, and indicators for urban-rural classification. For these variables, except for the urban-rural classification, weather damages, and extreme weather exposure, I include three lagged terms. I estimate the coefficients with and without the county and state-year fixed effects. The results reported in Table I do not indicate that these variables can predict the likelihood that a PADDD will occur. In fact, other than the 3-year lagged personal income and the trend in population change, none of the coefficients are statistically or economically significant.

II. Weather Damages Robustness Tests

In this section, I reproduce the analysis in Table XII of the main paper utilizing propensity score matching. This analysis is used to shed light on the effect of natural capital loss on weather damages a county experiences. Specifically, I first restrict the matches to counties in the same state, with the same urban-rural classification and coastal indicator. Next, I use propensity score to identify the best counterfactuals to the treated counties (i.e., those that experience a natural capital loss event) using the following county characteristics: extreme weather exposure in the past five years, density, population, trends in population, personal income, natural capital size (protected area), and Atlantic region indicator. The final sample includes 182 treated counties and 364 control counties since I limit the matched control to two counties for each treated observation. Lastly, I use the approach from Boulongne et al. (2020) as in Equation (6) of the paper. The result is qualitatively similar to Table XII of the main analysis. Specifically, counties that experience a natural capital loss event report greater weather damages after the PADDD event compared to non-PADDD counties.

III. Municipal Bonds Robustness Tests

In this section, I present the results of the difference-in-difference analysis presented in section V.C. of the paper by splitting the sample into the pre- and post-PADDD periods. The results reported in Table III are qualitatively similar to the estimates presented in this section.

In addition, I report the analysis on municipal bond spreads. Following Goldsmith-Pinkham et al. (2020), I utilize the AAA-rated tax-exempt benchmark curve from 2005 to 2019 to compute the municipal bond credit spread. The results are qualitatively similar to Table XIII in the main analysis. Table IV shows that the difference in spreads between treated and control areas turns from negative to positive after the extreme weather event for all months except for Months 3 and 4. In fact, the difference in spreads might be negative in the period before the disaster due to confounding features such as proximity to nature or the coastline that promote better economic circumstances (i.e., lower economic risk). However, after an extreme weather event, the difference turns positive, suggesting that counties facing natural capital loss suffer more severe weather damages than similar non-PADDD areas.

The economic magnitude of this difference is significant since the spreads change from an average of -9 basis points in the pre-period to 11 in the post-period. The difference between column (1) and the other two is that the reference month is the month before the weather event in column (1) and the month two periods before the event in columns (2) and (3). I utilize $t-2$ as a reference since some extreme weather events could be forecasted in advance and markets might reflect this forecast accordingly.

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Goldsmith-Pinkham, P. S., M. Gustafson, R. Lewis, and M. Schwert (2020). Sea level rise exposure and municipal bond yields. *Available at SSRN 3478364*.

Table I. Logit Estimation of PADDD Events

This table reports the logit estimation coefficients with the PADDD indicator as dependent variable. The variables utilized to predict the natural capital loss event are urban-rural classification (indicator), personal income (including year $t-2$ and $t-3$), unemployment rate (including year $t-2$ and $t-3$), population (including year $t-2$ and $t-3$), density (including year $t-2$ and $t-3$), $Weather\, Exp._{1-5}$, $Weather\, Exp._{6-10}$, change in population, and population trend. All variables are lagged by one year before the PADDD event unless otherwise specified. The specifications in column (2) include county and state-year fixed effects. The standard errors are clustered at the state level. t-statistics are reported in parenthesis. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

	(1)	(2)
Small Metro	-0.903	-1.368
	(-0.67)	(-0.99)
Micropol.	-1.170	-1.584
	(-0.88)	(-1.17)
Noncore	-1.729	-2.092
	(-1.30)	(-1.55)
Weather Exp.$_{1-5}$	0.032	-0.028
	(0.98)	(-0.66)
Weather Exp.$_{6-10}$	-0.198	-0.142
	(-1.24)	(-0.65)
Annual Damages	-0.002	-0.002
	(-1.04)	(-0.92)
Personal Income	0.000	0.000
	(0.51)	(0.32)
Personal Income$_{t-2}$	0.000	0.000
	(-1.40)	(-1.24)
Personal Income$_{t-3}$	0.000***	0.000***
	(-3.58)	(-3.47)
Unemployement	0.42	0.73
	(0.28)	(0.61)
Unemployement$_{t-2}$	0.10	0.17
	(0.54)	(0.58)
Unemployement$_{t-3}$	0.04	0.28
	(0.43)	(0.35)
Pers. Inc. Change	0.531	0.043
	(0.17)	(0.01)
Trend in Lagged Pers. Inc.	0.438	0.475
	(0.15)	(0.16)
Population	0.000	0.000
	(-0.21)	(-0.24)
Population$_{t-2}$	0.000	0.000
	(0.27)	(0.25)
Population$_{t-3}$	0.000	0.000
	(0.02)	(0.15)
Pop. Change	-1.607	-1.457
	(-1.24)	(-1.23)
Trend Pop.	-4.185*	-5.605*
	(-1.47)	(-1.49)
Density	-0.005	-0.006
	(-0.73)	(-0.75)
Density$_{t-2}$	-0.017	-0.018
	(-0.48)	(-0.36)
Density$_{t-3}$	0.010	0.008
	(0.49)	(0.25)
Fixed Effects	N	Y
Observations	143,961	12,442

Table II: Estimation of Annual Damages using Propensity Score Matching
This table reports the coefficients of the regression estimation for the matched sample with annual damages as dependent variable and PADDD as exogenous shock. The counties must have the same coastal indicator (1 if a county is on the coast), be in the same state, and same urban-rural classification in order to be matched. The variables used for the propensity score calculations are the following: personal income, unemployment rate, population, density, trend in population ($t-2$ to $t-1$), $Weather\,Exp._{1-5}$, natural capital size (protected area), and Atlantic region indicator. The t-statistics are reported in parenthesis. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

	(1)
$Treated \times Post$	21.82**
	(1.71)
Treated Counties	182
Control Counties	364

Table III: Difference-In-Difference Estimation of Municipal Bond Yields - Pre/Post-PADDD Analysis

This table reports estimates of the coefficients of the difference-in-difference model collapsed into pre-PADDD and post-PADDD periods. The dependent variable is the monthly volume-weighted municipal bond yield. The Treated variable represents bond issued in counties that experience a PADDD event. Post is an indicator equal to one for observations occurring after the PADDD and zero otherwise. The controls include urban-rural classification (indicator), personal income, unemployment rate, population, density, $Weather\,Exp._{1-5}$, coupon rate, bond rating, years to maturity, and size of the bond issue. The specifications include county and state-year fixed effects. The standard errors are clustered at the state level. t-statistics are reported in parenthesis. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

	(1)	(2)	(3)
Treated × Post	0.032***	0.031***	0.035***
	(5.41)	(5.28)	(5.54)
Controls	Y	Y	Y
Population	N	Y	Y
Density	N	Y	Y
Personal Income	N	N	Y
Bond Characteristics	Y	Y	Y
Observations	257,261	205,105	205,105

Table IV. Difference-in-Difference Estimation of Municipal Bond Yield Spreads - Extreme Weather Event

This table reports the difference-in-difference estimation coefficients with monthly volume-weighted municipal bond yield spreads as dependent variable and extreme weather events as exogenous shock. The Treated variable indicates municipal bonds of counties that experienced a PADDD event no earlier than three years before the disaster. The controls include urban-rural classification (indicator), personal income, unemployment rate, population, density, $Weather\,Exp._{1-5}$, intensity of the weather event, coupon rate, bond rating, years to maturity, and size of the bond issue. The specifications include county and state-year fixed effects. The standard errors are clustered at the state level. t-statistics are reported in parenthesis. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

	(1)	(2)	(3)
Treated x 1(Month −5)	−0.339**	−0.323***	−0.323**
	(−2.41)	(−8.99)	(−2.20)
Treated x 1(Month −4)	0.002	−0.006	−0.006
	−0.03	(−0.24)	(−0.10)
Treated x 1(Month −3)	0.04	0.036	0.036
	(1.04)	(1.37)	(0.87)
Treated x 1(Month −2)	0.062	-	-
	(1.35)	-	-
Treated x 1(Month −1)	-	0.051***	0.051
	-	(4.55)	(1.06)
Treated x 1(Month 0)	0.046	0.044***	0.044
	(0.99)	(6.65)	(0.88)
Treated x 1(Month 1)	0.078	0.068***	0.068
	(1.48)	(6.51)	(1.15)
Treated x 1(Month 2)	0.110***	0.113***	0.113***
	(3.44)	(6.42)	(3.27)
Treated x 1(Month 3)	−0.002	−0.005	−0.005
	(−0.03)	(−0.17)	(−0.07)
Treated x 1(Month 4)	−0.036	−0.019	−0.019
	(−0.40)	(−0.49)	(−0.16)
Treated x 1(Month 5)	0.089**	0.089	0.089**
	(2.66)	(1.56)	(2.44)
Controls	Y	Y	Y
Personal Income	Y	N	Y
County FE	Y	Y	Y
State-Year FE	Y	Y	Y
Observations	205,105	257,761	205,105

Table V: Matching Estimation of Municipal Bond Yields - Pre/Post Extreme Weather Event - Neighboring Counties Only

This table reports the coefficients of the matching estimation. The sample of treated counties includes counties in a 50-miles radius from a county that experienced a natural capital loss event. The dependent variable is the monthly volume-weighted municipal bond yield. The Treated variable indicates municipal bonds of counties that experienced a PADDD event. Post is an indicator equal to one for observations occurring after the extreme weather event and zero otherwise. The matching variables include personal income, rate, population, density, $Weather\ Exp._{1-5}$, natural capital size, coupon rate, bond rating, years to maturity, and size of the bond issue. The standard errors are clustered at the bond level. t-statistics are reported in parenthesis. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

	(1)	(2)	(3)
Treated x Post	0.353*	0.424***	0.209***
	(2.03)	(3.97)	(5.75)
Treated x Post x Physical	0.401***	0.217*	0.767***
	(3.25)	(1.77)	(7.35)
Treated Bonds	-	1,999	161
Control Bonds	-	3,576	322
Physical Bonds	-	2450	234
Non-Physical Bonds	-	3,125	249
County Controls	Y	Y	N
Bond Controls	Y	Y	Y
Same County, Same year	N	N	Y
Fixed Effects	Y	-	-
Observations	559,144	182,470	40,207

Table VI: Estimation of Natural Capital Loss Effect on Farming Counties

This table reports the difference-in-difference estimation coefficients with monthly volume-weighted municipal bond yields, personal income, and population as dependent variables and PADDD as exogenous shock. The sample of treated counties includes counties in a 50-miles radius from a county that experienced a natural capital loss event. The main independent variables are the triple interactions between Treated, Post, and the farming indicator. The Treated variable indicates counties that experienced a PADDD event. The farming indicator equals 1 if the county is classified as economically dependent on farming by the BEA. The controls include urban-rural classification (indicator), personal income, unemployment rate, population, density, and coupon rate, bond rating, years to maturity, and size of the bond issue. The specifications include county and state-year fixed effects. The standard errors are clustered at the state level. t-statistics are reported in parenthesis. The symbols *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

	(1)	(2)	(3)
Treated x Post	0.114*	−0.075	−1.21**
	(1.78)	(−0.65)	(−1.69)
Treated x Post x Farming	0.165*	−0.276**	−0.30
	(1.88)	(−2.62)	(−1.54)
County Controls	Y	Y	Y
Bond Controls	Y	-	-
Fixed Effects	Y	Y	Y
Observations	559,148	188,409	188,331