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

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Abstract

This paper examines the value of climate change mitigation strategies such as nature conservation in municipal bond markets. Using extreme weather and natural capital loss shocks, I find that the market starts to price the value of natural capital after an extreme weather event. In fact, natural capital protection could decrease the county's cost of debt by between $3.2 and $6 million over the life of an average bond. Bonds tied to specific infrastructure projects are more affected than general-purpose bonds. The effects of mitigation strategies impact the county with the natural capital and its neighbors. More broadly, I find that natural capital loss is related to population migration and a decrease in personal income, with counties dependent on farming suffering the most. Overall, this paper shows that financial markets price the value of mitigation and highlights the critical role of nature as a shield from natural disasters.

Keywords: Climate Change, Environmental Valuation, Municipal Bonds, Municipal Financing, Natural Disasters.

JEL classification: G14, H74, Q54, Q56.

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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 studies have underscored the connection between human activity, global warming, and the increase in natural disasters' strength and frequency (Van Aalst (2006), National Academies of Sciences et al. (2016)). Consequently, governments and businesses have implemented policies targeted to reduce the impact of human activity on the planet. However, even if humanity were to stop all CO_2 emissions today, we would still experience the effects of global warming for the coming decades. For these reasons, local climate change mitigation strategies such as nature conservation are crucial to diminish the economic losses due to climate change. However, local mitigation strategies have received relatively lower attention in the climate change literature (Bouwer et al. (2007)). Estimating the value of natural mitigation strategies is essential for assessing the financial impact of local climate change risk as well as evaluating the trade-offs between nature conservation and economic development.

In this paper, I exploit the advantages offered by municipal bond markets to examine whether local mitigation strategies, in particular nature conservation, are priced in financial markets. Municipal bonds provide an ideal setting for studying this question since investors need to account for local climate-related risks when pricing these assets. As opposed to firms, municipalities cannot move to avoid climate change risk and need to rely on mitigation strategies. This local risk affects tax revenue and the likelihood that a municipality can repay the bonds issued. Hence, I can use the municipal bond market to infer the value of nature conservation as a mitigation strategy to the risk of weather calamities. On the other hand, municipal bonds trade sparsely, with an average of 2.88 trades per year. To overcome this limitation and perform the event study, I compute county-level volume-weighted average bond yields as well as estimate a repeated sales model as proposed by Auh et al. (2021).[1]

Quantifying the value of natural capital is difficult for a few reasons.[2] First, natural capital is inherently a non-traded asset. In addition, the presence of natural capital might be correlated with time-varying local economic conditions. To circumvent these problems, I identify the mitigation value of natural capital using a quasi-experiment setup that exploits local extreme weather shocks and natural capital loss events. 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.[3]

The results show that the market does not price the value of natural capital until an extreme weather event hits. In particular, the yield spread between counties that experience a natural capital loss and those that do not, i.e., mitigation premium, increases from effectively zero to an average of 17 basis points (5.71% of average yield). The effect of mitigation (or lack thereof) could increase the municipality's cost of debt by between \$3.2 and \$5.9 million over the life of the bond.[4] Moreover, bonds used to fund infrastructure projects and those issued by farming-dependent counties display the highest increases in yields. The effects of natural capital loss are also reflected in neighboring counties and other macroeconomic indicators such as population migration and personal income.

This study is the first to identify a mitigation premium and quantify the economic value

[1] Among many others, see Case and Shiller (1987), Goetzmann (1992), Francke (2010), and Garzoli et al. (2021) for examples of repeated sales models in real estate. For corporate bonds applications, see Spiegel and Starks (2016) and Robertson and Spiegel (2017).

[2] Economists have considered natural resources as an asset or capital stock that provides a series of services or "income," and the depletion or destruction 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.

[3] Figure 1 provides a graphical representation of this example.

[4] This back-of-the-envelope calculation utilizes the in-sample average bond yield and maturity, the estimated mitigation premium for all bonds and revenue bonds, and the average annual county bond issuance.

of natural capital on municipal bond markets. Overall, the results provide exciting insights regarding the value of natural capital as a mitigating green infrastructure and nature's economic value for the fight against global warming. This analysis has clear policy implications for local and state governments as it pertains to the importance of nature conservation.

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. The study shows that the pricing of SLR risk began 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.

Another strictly related study is the one by Auh et al. (2021), which analyzes the effect of natural disasters on municipal bonds. In particular, they utilize the repeated sales approach to overcome the lack of recorded bond transactions at a high enough frequency. The results show that counties hit by natural disasters experience lower bond returns mainly driven by revenue bonds. My paper complement these insights by exploring the implications of mitigation strategies for counties facing natural disaster risk.

As it pertains to mitigation from climate change in the finance setting, 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 results reported in this paper also complement the general and growing literature on 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.

This paper relates to the environmental literature and the studies on nature conservation. A strand of the conservation literature has investigated the widespread downgrading, downsizing, and degazettement (loss of legal protection for an entire protected area) and how these phenomena affect nature's ability to protect essential habitats, contribute to the alleviation of climate change, and the general 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 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: higher cost of debt, increased weather damages, population migration, and lower personal income.

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.[5] 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. (2021), Johnson et al. (2020), Nguyen et al. (2020), Rezaie et al. (2020), Walls et al. (2020), Chang et al. (2021) and Costanza et al. (2021) focus their attention on protected areas (PAs) and mitigation from storms 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 and natural capital.

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 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

[5] See 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. (2021), Johnson et al. (2020), Nguyen et al. (2020), Rezaie et al. (2020), Walls et al. (2020), Chang et al. (2021), and Costanza et al. (2021).

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 avoided 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.[6]

Overall, the results proposed in the paper highlight the effects of natural capital loss for the municipalities' cost of debt and local economies. The analysis informs policymakers about the relationship between climate change risk, local cost of debt, and nature conservation. Understanding the relationship between mitigation and local climate change risk in municipal bond markets allows estimating the value investors assign, if any, to mitigation and the risks related to global warming. Also, this paper contributes to the literature on natural capital valuation. In fact, the market reaction to natural capital loss approximates the value of nature conservation in financial markets as it pertains to mitigation from extreme weather.

The remainder of the paper is organized as follows. Section II offers some anecdotal

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

evidence related to the importance of protected areas and an example of PADDD. Section III provides a description of the data and summary statistics. Section IV includes the empirical approach, the results, and a series of robustness tests. Finally, Section V discusses the implications of the study.

II. Background

A. 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 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 cost 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)).

B. 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. Data and Summary Statistics

A. *Weather Damages*

The National Oceanic and Atmospheric Administration (NOAA) collects data on crop and property damage (in US dollars) caused by weather events. For this study, I use the period starting in 1969 and ending in 2020.[7] 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. *Protected Area Downgrading, Downsizing, and Degazettement*

One of the critical datasets 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)).[8]

[7]The data can be found here: `https://www1.ncdc.noaa.gov/pub/data/swdi/stormevents/csvfiles/`.
[8]The appendix contains a brief history of the development of the National park system in the US.

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)).[9]

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 US 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 5 and 6 show the location of the PAs that have been downgraded, downsized, or degazetted during the sample period starting from 1976 to 2020. This sample period is used for the analysis of weather damages, population migration, and personal income. For the analysis of municipal bonds, I use the sample period from 2005 to 2020 due to the limited time series for municipal bond information. During the 1976-2020 period, 94% (405) of the county events are downgradings. Instead, from 2005-2020, the downgrades comprise 92% (289) of the sample. The remaining events in both sample periods are downsizings and there

[9] A graphical representation of the PADDD is reported in Figure 4.

are no degazettements from 1976 to 2020 in the US.

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 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, 31,859 km^2 (12,300 mi^2) is about the size of Belgium or the equivalent of nine Yellowstone National Parks.[10] Going forward, I will discuss the summary statistics related to the 2005 to 2020 sample, given that the main focus of this study is the municipal bond market. [11]

It is also interesting to notice that more than half of the PADDD is concentrated in rural areas. In fact, for the period from 2005 to 2020, about 58% of the events and 41% of the area affected is in urban areas classified as micropolitan or noncore (Table III).

With respect to the geographical distribution of PADDD events, Table IV shows that, in the period from 2005 to 2020, the states with the most events are Arkansas, California, Florida, Washington, New Mexico. Moreover, 45 of the 48 contiguous states experience at least one PADDD event in the sample period.

The WWF dataset also includes the reported cause of PADDD. Table V highlights how the main reason for PADDD is characterized as subsistence, defined as non-commercial or small-scale commercial, artisanal, or non-industrial (non-mechanized) extraction or production activities.[12] Moreover, a smaller portion of the natural capital loss 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 down-

[10] If we include Alaska and Hawaii, the size of the PADDD in 2016 is 103,231 km^2, or as large as Iceland or 30 Yellowstone parks.

[11] The PADDD summary statistics for the 1976 to 2020 sample are available in the appendix.

[12] The definitions for all causes of PADDD is reported in the appendix.

grade, downsize, or degazettement of a protected area needs to be approved by the federal government.[13]

C. 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.[14] 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 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. In addition, evidence from the environmental literature shows that natural areas such as forests and wetlands are extremely successful in mitigating extreme precipitation events and tropical cyclones.[15] Lastly, scholars have highlighted how a warming climate will bring together more extreme precipitation (Allen and Ingram (2002),Wu et al. (2013), and Donat et al. (2016)). Section IV contains a more detailed discussion of the natural disaster exposure measure.

D. 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

[13] In the appendix, I provide additional discussion regarding why natural capital loss events might happen.
[14] `http://www.columbia.edu/~ws2162/links.html`.
[15] See footnote 5.

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.[16] 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, 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.

Finally, I collect the municipal bonds AAA-rated tax-exempt benchmark curve from 2005 to 2020 from Bloomberg and use it as a benchmark for the municipal bond credit spread analysis.[17] 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.

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

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

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.

Also, 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 control for within-county heterogeneity in disaster exposure.[18]

E. National, State, and Local Parks

To ensure that the matching analysis accounts for important observable county characteristics as it pertains to natural capital, I collect the protected area of each county using the Protected Area Database (version 1.4) from the United States Geological Survey.[19] 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.[20]

This information is important because it allows comparing counties with similar-sized protected areas. Unfortunately, these data can be used only as a time-invariant specification for the matching algorithm 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.

[18]The appendix contains a complete list of the use of proceeds that are classified as "physical" and "non-physical."

[19]`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`.

[20]Further detail regarding this dataset is available in the appendix.

F. County Data

The county-level economic and population data are collected from the US Bureau of Economic Analysis (BEA) and the US Bureau of Labor Statistics (BLS). For this study, I utilize county-level population, personal income, and unemployment rate. The sample period utilized starts in 1969 and ends in 2020. 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 sources. The employment rate is defined as the ratio of employed people and the total labor force. I also collect information on the counties' economic characteristics from the Economic Research Service of the US Department of Agriculture. Specifically, I utilize the 1979, 1986, 1989, 2004, and 2015 County Typology Codes. These codes classify all US 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.

I supplement the county economic information with financial information from the Census of Governments, which reports local government debt, cash and securities, and tax revenue. Specifically, I measure revenue concentration using general revenue information, including intergovernmental (IG) revenue from the federal government, IG revenue from the state government, and local revenue. These three sources of revenue are utilized to compute the Hirfindahl-Hirchman index (HHI) to define revenue concentration. Next, I construct quintile indicators for the debt-to-tax-revenue ratio and revenue concentration.

Lastly, I estimate the county's elevation and distance from the coast based on its centroid coordinates.

G. FEMA Federal Disaster Aids

I collect data on federal disaster aid to households and local governments from the Federal Emergency Management Agency (FEMA). Also, I utilize the information on presidential disaster declaration to identify disaster location, declaration date, and the amount approved for disaster aids. Counties included in a presidential disaster declaration are eligible for public assistance, individual assistance, and/or hazard mitigation grants. The public assistance program funds local governments to allow repairs for damages caused by disasters. The individual assistance program targets homeowners and renters who experience damages from disaster events. Lastly, the hazard mitigation assistance program funds project aimed at preventing future disasters.

The information for the public assistance and hazard mitigation assistance programs is at the project level and includes the county, disaster date, total project cost, and federal contribution to the project. Instead, the individual assistance program data is at the zip-code level. I aggregate the information from all three programs and compile a measure of county-year federal disaster transfers similar to Auh et al. (2021) (i.e., FEMA Transfers). Next, I classify the sample into two groups, below-median and above-median FEMA transfers, creating a dichotomous indicator variable.

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

IV. Empirical Analysis

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

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, nature is particularly effective in reducing the damages from heavy precipitation.[21] Economists have utilized various physical weather measures (wind speed, rainfall, or storm surge) to preserve the exogenous nature of the shock (Noy (2009) and Hsiang and Jina (2014)). For instance, many studies use only hurricanes as extreme weather events. 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.

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

[21] See footnote 4.

$Weather\ Exp._{c,\,t}$ 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 US are exposed to very different threats from global warming, as diverse as wildfires, hurricanes, and droughts. Consequently, each counties' past exposure affects how 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 and mitigating infrastructure. The measure I propose accounts for 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. County-Level Bond Yields

As highlighted by Auh et al. (2021), municipal bonds trade infrequently with an average of 2.88 trades per year. For this reason, running an event study would yield biased estimates. In order to overcome this complication, I compile a yield measure at the county level using a volume-weighted average of bond yields. This allows me to estimate the county-level effect on municipal bond yields during an extreme weather event.[22]

[22] For robustness, I perform a similar analysis to Auh et al. (2021) using the repeated sales approach.

C. Identification

In this section, I examine the pricing implications of natural capital loss on municipal bonds. Investors should account for the value of natural capital when pricing municipal bonds since nature provides mitigation from extreme weather and climate change risk. Consequently, municipal bonds of counties that experience natural capital loss should be trading at a premium, irrespective of the timing of an extreme weather event. However, I conjecture that the importance of natural capital might become salient to investors only after a shock to local climate change risk. I test this hypothesis using a quasi-experiment setup. I study the behavior of municipal bond markets around an extreme weather event. In this analysis, I compare counties that experienced a loss in natural capital to those that did not using county-level volume-weighted average yields of municipal bonds.

As briefly discussed in the introduction and figure 1, the ideal experiment would entail comparing counties, county A and county B, with similar characteristics and natural capital stock. At time t, county B loses part of its natural capital and at time $t+1$, an extreme weather event hits both counties. This empirical design aims to compare municipal bonds that trade in the same year and state and have similar observable characteristics, except for having experienced a natural capital loss event or not.

The sample includes counties that experienced extreme weather events and that contain protected areas.[23] Also, The sample excludes treated counties from the control group in future periods to avoid negative weights for the average treatment effects (ATE) in the presence of heterogeneous treatment effects as highlighted by Borusyak and Jaravel (2017) and De Chaisemartin and d'Haultfoeuille (2020).[24]

I select extreme weather events using the precipitation measure presented in section IV.A. The months selected as extreme weather events are months in which a county experienced

[23] I define protected areas using the Protected Areas Database of the United States (PAD-US). More details regarding this dataset is available in the appendix.

[24] I follow this step in all difference-in-difference estimations presented in this paper and the appendix.

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 difference-in-difference model used for the estimation of the natural capital effect after an extreme weather event:

$$Avg.Yield_{c,t} = \sum_{t=-5}^{5} 1(Month = t) \times \gamma_t Treated + \theta_t{}' X_{c,t} + \delta_{s,t} + \epsilon_{c,t}, \tag{2}$$

for county c in month t. $Treated$ is an indicator for a county that has experienced natural capital loss and X represent a vector of control variables. Lastly, $\delta_{s,t}$ represent state-year fixed-effects.

The coefficient of interest is γ_t, which represents the difference in average 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 within three years before the weather event. The vector of controls includes $Weather\ Exp_{1-5}$ which represents the natural disaster exposure from year $t-1$ to $t-5$.[25] This variable reduces the concern that the results reported are caused by differences in pre-existing disaster mitigation programs implemented by more exposed counties.

Moreover, X controls for county characteristics (urban-rural classification, population, density, personal income, unemployment rate, ratio of protected area to total county area, proximity to the coast, elevation, quintile indicators for debt-to-tax-revenue ratio and revenue concentration, dichotomous indicator for FEMA transfers, and trend variables ($t-2$ to $t-1$) for population, density, personal income, and unemployment rate), municipal bond characteristics averaged at the county level (coupon rate, rating, years to maturity, years since issuance, size of the bond issue, and the ratio of trading volume to amount outstanding),

[25] This measure is calculated using the maximum standardized precipitation (equation (1)) 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.

and the intensity of the weather event.[26] The use of state-year fixed effects allows controlling for time-varying local economic conditions. Hence, the coefficient estimates are identified from the difference in yields of bonds issued in the same state and trading in the same year.

D. *Main Results*

Table VII reports the results of the difference-in-difference analysis. Column (1) includes all bonds in the sample and, in columns (2) and (3), I split the sample in revenue and general obligation bonds, respectively. I utilize $t-2$ as a reference since some extreme weather events could be forecasted in advance and markets might reflect this forecast accordingly.

The coefficients in columns (1) to (3) show that the difference between treated and control counties turns from statistically indifferent from zero to positive and significant after the extreme weather event for all months except for one (month 4). In other words, counties that lose natural capital display a "mitigation premium" compared to similar counties that do not experience natural capital loss. As we can see, the effect is stronger for revenue bonds (column (2)), possibly because these bonds are backed by the revenue of the specific project and not by the overall municipal tax revenue.

The economic significance of these results is large. In fact, the yields change from statistically indifferent from 0 to between 11 and 22 basis points, which corresponds to an average pre-post spread of 5.7% of an average bond yield (3.04%). To better understand the impact of the mitigation premium, 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, an average county with $119.72 million in annual municipal bond issuance could save an average of $207,913 in annual coupon payments if they "protect" their protected areas

[26] The National Center for Health Statistics (NCHS) classifies counties into six urban-rural categories: large central metropolitan areas, large fringe metropolitan areas, medium metropolitan areas, small metropolitan areas, micropolitan areas, and noncore. See appendix for further details. The quintile indicators for the debt-to-tax-revenue ratio, revenue concentration, and FEMA transfers are included following the insights in Auh et al. (2021). I control for the pre-trends and ex-ante county characteristics to satisfy the parallel trend assumption.

and \$3.21 million over the average life of the bonds.[27] The effect is much larger for revenue bonds with an average annual savings of \$389,289 and \$6 million over the average life of the bonds.[28]

I also show in Table VIII 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 ($Weather\ Exp.$). As we can see, the results are similar when aggregating the time period to pre- and post-disaster. Moreover, the intensity of the disaster is important when considering the change in the local cost of debt related to climate change risk.

Although unlikely, the results could be confounded by the intensity of extreme weather events in areas affected by natural capital loss. In other words, if, during the sample period, counties that experienced PADDD also randomly experienced stronger weather events, the results would not be driven by natural capital loss but by the difference in the strength of the weather event. To diminish the concern from this possible source of bias, I control for extreme weather event intensity and analyze the difference in weather intensity between the two samples. Specifically, I compare the monthly raw and the standardized precipitation for the event months used in the difference-in-difference estimation for counties that experienced natural capital loss and those that did not. The differences between the two measures for the two samples are statistically indifferent from zero (0.098, t stat=0.096 ; 0.017 t stat=0.093).

It is relevant to note that there are some discrepancies between the results in Table VII and those reported in Auh et al. (2021). Specifically, the authors find that natural disasters do not affect general obligation bonds except for specific local financial conditions. This difference could originate from two sources. First, I utilize precipitation, a purely exogenous event, to identify shocks to the county's climate change risk awareness compared to the normalized damage measure used in Auh et al. (2021).

Second, the definition of treated and control groups between the two studies is differ-

[27] $0.174\% \times \$119.72$ million $\times$ 15.43 years.

[28] These estimates do not account for the opportunity cost of not using the land for economic activity.

ent. Specifically, I only include counties that experienced a natural disaster event and the treatment is identified using natural capital loss. On the other hand, Auh et al. (2021) are interested in estimating the effect of natural disasters and, for this reason, they compare counties hit by weather damages to similar counties not hit by a disaster and at least 500 miles away. Consequently, it is plausible that counties affected by natural capital loss have increased climate risk exposure, which increases the overall risk of future county's cash flows, conditional on being hit by a weather event. This latter assumption does not hold for the treatment and control in Auh et al. (2021); it is not necessary for their study and does not affect their results.

D.1. Discussion on the Exogeneity of PADDD

A discussion on the exogeneity of the natural capital loss events is necessary. A few reasons suggest that these natural capital events are exogenous. Specifically, PADDD needs to be approved at the federal level and, for this reason, it is hard to argue that the causes of PADDD are specific to the county. In other words, unobservable time-varying county-level characteristics such as diminishing natural resources or worsening crop yields for farming communities cannot justify the enactment of a PADDD. In addition, I identify the effects of natural capital loss at the state level using state-year fixed effects. Moreover, I utilize county fixed effects for bond level analysis. These fixed effects take into account time-invariant unobservable county characteristics and time-variant unobservables at the state level. Moreover, the matching strategy using ex-ante county characteristics and trends as well as the analysis using the same county provide robustness to the main results.[29]

Also, after running a logit model, I am not able to identify observable predictors of

[29] See robustness section.

PADDD.[30] Lastly, 75% of the area affected by PADDD is caused by subsistence (non-commercial or small-scale commercial, artisanal, or non-mechanized extraction or production activities for local or personal consumption). These events do not seem to be related to local unobservable economic trends and characteristics.

To diminish further the endogeneity concerns due to non-random treatment, I use extreme weather events as purely exogenous weather-related shocks to local economic activity and climate risk awareness to identify the mitigating effect of nature. At a minimum, the results reported are the manifestation of a treatment effect on the treated.

E. Discussion of the Channel - Natural Capital Loss and Weather Damages

In order to clarify the drivers of the mitigation premium, I investigate the relationship between natural capital loss and weather damages. Formally, I hypothesize that counties that experience 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.[31] 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 for the period starting in 1969 and ending in 2020. Following is the model utilized for the estimation of the natural capital effect.

$$\begin{aligned} Damages_{c,\,t} = \alpha + \gamma_1 Treated \times Post + \gamma_2 Treated + \gamma_3 Post \\ + \gamma_4 Weather\,Exp_{1-5} + \theta_t{}' X_{i,t-1} + \delta_c + \delta_{s,t} + \epsilon_{c,t}, \end{aligned} \tag{3}$$

[30] The logit model contains the following independent variables: personal income, population, unemployment, population change, density, density change, weather damages, indicators for urban-rural classification, debt-to-tax-revenue ratio, revenue concentration, and FEMA transfers. For these variables, except for the urban-rural classification, I include three lagged terms. I also include the county and state-year fixed effects. More details are available in the appendix.

[31] The research that describes this relationship is mentioned in the introduction.

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.

For this analysis, I consider an event window that starts five years before the PADDD event and ends five years after. The controls include the same time-varying county characteristics mentioned in the previous section. Also, I control for local weather exposure to account for heterogeneity in disaster vulnerability. 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.

Table IX reports the difference-in-difference and matching estimates for the annual damages. In regards to the regression set up in columns (1) and (2), I find that counties affected by a loss in natural capital experience greater weather damages. The coefficients are economically and statistically significant. In fact, after a PADDD event, a treated county experiences \$9.7 million in damages more than a similar county in the control group.

To alleviate the concerns from selection bias and heterogeneous treatment effects, in addition to the fixed-effect model and difference-in-difference estimation, I estimate the effect of natural capital using matching.[32] First, I restrict the matches to counties in the same state and with the same urban-rural classification. Next, I utilize propensity score matching (PSM) to find the best counterfactual for each treated county (those that experienced a natural capital loss event) using the ex-ante characteristics.[0] The variables used are the following: county extreme weather exposure in the past five years, density, population, personal income, unemployment rate, tercile indicators for debt-to-tax-revenue ratio and revenue concentration, a dichotomous indicator for FEMA transfers, natural capital size

[32]See Callaway and Sant'Anna (2021), Sun and Abraham (2020), and De Chaisemartin and d'Haultfoeuille (2020) for a discussion on event studies with heterogeneous treatment effects.

[32]For robustness, I utilize nearest neighbor matching. The results are reported in the appendix.

(protected area), and trend in population.

The final sample includes only the matched control and treated observations. The results in column (3) are estimated using the regression:

$$Damages_{c,t} = \alpha + \gamma_1 Treated + \gamma_2 Post + \gamma_3 Treated \cdot Post \,, \tag{4}$$

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 of the matching are reported in column (3). We can see that the matching estimates are even larger in magnitude. The counties that experienced natural capital loss report statistically significant higher annual damages of $23.75 million.

A possible source of bias in the results could be originating from the correlation between weather damages and the county's economic activity. 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 the real estate prices. This index represents the typical value of homes in the 35^{th} to 65^{th} percentile range. Figure 8 shows that there is no relation between the extreme weather measure and real estate prices, which proxy for local economic conditions.[33]

Lastly, the results could also be influenced by the construction of new infrastructure in place of the protected area. Specifically, in the 1976 to 2020 sample, 33% of PADDD are enacted for infrastructure projects. Consequently, at least part of the natural capital is

[33] These results are different from Goldsmith-Pinkham et al. (2020), which 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.

replaced with some construction (e.g., roads, power lines, bridges) which can be damaged during extreme weather. To diminish this concern, in unreported results, I use only natural capital loss events related to subsistence which entail very minimal or no constructions. The results are qualitatively similar to the ones proposed.

F. Additional Results

F.1. Physical vs. Non-Physical Use of Proceeds

In this section, I exploit the heterogeneity in the use of proceeds to study the cross-sectional effect of natural capital. Specifically, I classify bonds into physical and non-physical use of proceeds as discussed in Section III.D. I hypothesize that bonds with physical use of proceeds are more exposed to climate risk. This is because the bond is directly tied to a project that could be damaged by extreme weather. Consequently, if natural capital provides mitigation from extreme weather risk, the effect of the loss of natural capital should be more pronounced in bonds with the physical use of proceeds. I utilize the same difference-in-difference model, except that I add a triple interaction term between Treated, Post, and the physical indicator, and I perform the analysis at the bond level. Since municipal bonds trade infrequently, I aggregate the yields into a volume-weighted average for the pre and post-period, respectively. Moreover, trades executed closer to the event month receive greater weighting. The results in Table X column (1) show that bonds with physical use of proceeds increase in yields 14 basis points more than non-physical bonds. It is relevant to notice that the bond-level coefficients on the term Treated $\times$ Post are qualitatively similar to the county-level estimations, providing robustness to the main results.

To provide robustness to the results, I estimate the cross-sectional effect of natural capital on bonds using matching. First, I restrict the matches to bonds issued in the same state with the same rating, type (general obligation or revenue), and county FEMA transfers indicator (i.e., below or above median FEMA transfers). I allow a maximum of two years difference in maturity and a maximum of six months difference in the extreme weather event date. Next, I utilize propensity score matching 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), debt-to-tax-revenue ratio, revenue concentration, trend in population, and bond coupon rate. Following is the model utilized for the estimation:

$$y_{i,t} = \alpha + \gamma_1 Treated + \gamma_2 Post + \gamma_3 Physical + \gamma_4 Treated \cdot Post \cdot Physical, \tag{5}$$

where *Physical* represents the indicator for physical use of proceeds. The coefficient of interest is γ_4 which represents the differential effect on physical projects.

The final sample includes only the matched control and treated observations. Specifically, the sample contains 651 unique bonds from counties that experienced a natural capital loss event and 1,218 comparable bonds of counties that did not experience a PADDD event. The estimates in Table X column (2) show that bonds issued for physical projects are more affected than the rest of the sample by 18 basis points. The results are qualitatively similar to the estimates without matching.

To provide even further evidence, 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 security'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, the effect of natural capital loss. On the other hand, this approach considerably limits the number of observations utilized for the estimation. The results in Table X column (3) describe similar magnitudes to the ones using matching on county characteristics, both regarding the overall impact of natural capital loss and the cross-sectional effect on physical bonds.

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

F.2. Spillover Effects

The effects of natural capital loss might not be limited to the county that possesses the natural capital. Due to the spatial and economic links between neighboring counties, even counties not directly impacted by natural capital loss might experience negative consequences during extreme weather events. In order to study this phenomenon, I 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.[34]

In column (1) of Table XI, I report the results of the regression analysis. Instead, columns (2) and (3) report the results of the matching estimation. The empirical approach used for this analysis is equal to the one described in section IV.F.1 and the only difference is the use of neighboring counties to define the treated and control group. The results in Table XI show

[34]The distances between counties are great-circle distances calculated using the Haversine formula based on internal points in the county. 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`).

that the effect is still persistent when including only neighboring counties in the estimation. Moreover, this suggests that the economic impact is more widespread since natural capital's mitigating effects extend to nearby counties. In addition, as shown in Table X, bonds issued for physical projects are the most affected.

F.3. County Economic Dependence

The U.S. Department of Agriculture classifies counties by their economic dependence. I exploit this county-level heterogeneity to analyze the cross-sectional effects of natural capital loss on 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 alleviating water stress.[35] For these reasons, I conjecture that counties more economically dependent on farming should be affected most by natural capital loss. In order to test this hypothesis, I perform two different event studies. In the first, i.e., column (1) of table XII, I use extreme weather events to define the shocks and natural capital loss to identify the treated and control groups. Instead, in columns (2) and (3), I control for weather exposure and utilize the natural capital loss event as shock and to define the treatment and control groups. [36] The regression specifications are identical to those presented in the previous sections.

The outcome variables analyzed are the county-level monthly volume-weighted average municipal bond yields (column (1)), annual personal income (column (2)), and annual population change(column (2)).[37] The results show that natural capital loss affects bonds issued by farming counties more than other counties and impacts other important economic outcomes, such as population migration and personal income. Specifically, farming counties

[35]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.

[36]For all specifications in this analysis, counties within a 25-miles radius from the county that loses natural capital are included in the treatment group.

[37]The sample period for the municipal bond analysis is from 2005 to 2020. Instead, the sample period for personal income and population change is from 1969 to 2020.

report higher yield increases of about 17 basis points than the rest of the sample. In addition, farming counties experience a further decrease of 0.34% in personal income (t stat: -2.82) and a -0.15% decrease in population (not statistically significant: t stat$=-1.38$). Overall, this analysis suggests that the consequences of natural capital loss are perceived in agricultural counties and can affect the whole country through food production.

G. *Additional Robustness Tests*

In addition to the cross-sectional evidence, the matching, and the robustness provided in the previous sections, I present additional robustness tests below.

For this reason, I compute the difference-in-difference estimator proposed by De Chaisemartin and d'Haultfoeuille (2020) using the Stata package *did_multiplegt*. I collapse the time-period in pre- and post-extreme weather event and utilize the five months before and after the event for the estimation. The results reported in Table XII of the appendix are qualitatively similar to Table VII. These results suggest that heterogeneous treatment effects do not undermine the paper's insights.

G.1. Placebo Test

To provide additional robustness to the results, I perform a placebo test using the estimator proposed by De Chaisemartin and d'Haultfoeuille (2020). Specifically, I select counties that experienced extreme weather events. Next, I consider counties as treated if the county will experience a natural capital loss event within three years after the extreme weather event. Lastly, I estimate the effects on all bonds as well as revenue and general obligation bonds separately. The results of the placebo test are reported in Table XIII. We can see that the difference between the pre- and post-period is close to zero and statistically insignificant. These results highlight that ex-ante differences between the treated and control group are not affecting the results.

G.2. Municipal Bond Credit Spread

Similar to Goldsmith-Pinkham et al. (2020), I repeat the main analysis of Table VII using the municipal bond credit spread. Specifically, I use the municipal bonds AAA-rated curve as a tax-exempt benchmark for the municipal bond credit spread analysis. In these specifications, the credit spread equals the bond yield minus the maturity-matched par yield from the AAA-rated curve. The results are reported in the appendix and are qualitatively similar to the results in the main analysis. Moreover, the economic magnitude is comparable to the Sea Level Rise Exposure effect reported in Goldsmith-Pinkham et al. (2020).

G.3. Repeated Sales

As proposed by Auh et al. (2021), another possible strategy to estimate the effect of natural disasters on municipal bonds is to utilize the repeated sales approach to construct county-level monthly bond returns. This empirical approach has been widely utilized in other sparsely traded assets such as real estate and corporate bonds (e.g., Case and Shiller (1987), Goetzmann (1992), Francke (2010), Garzoli et al. (2021), Spiegel and Starks (2016), and Robertson and Spiegel (2017)). First, I estimate the following repeat sales model to recover county-level bond returns.

$$p_{i,v} + CPN_{i,l:v} = p_{i,l} \prod_{t=l+1}^{v} (1 + r_t^c)\epsilon_{i,t}, \tag{6}$$

where $p_{i,v}$ and $p_{i,l}$ are the prices of bond i issued by county c in month v and l ($v > l$), respectively. $CPN_{i,l:v}$ represents the coupon payments from bond i occurred between month v and l. The county-level bond return at time t is r_t^c. $\epsilon_{i,t}$ represents the bond-specific idiosyncratic return. By taking the log of eq. (6), I obtain:

$$R_{i,l:v} = \sum_{t=l+1}^{v} (R_t^c)\, \epsilon_{i,l:v}, \tag{7}$$

where $R_{i,l:v} = log((p_{i,v} + CPN_{i,l:v})/p_{i,l}$, $R^c_t = log(1 + r^c_t$, and $\epsilon_{i,l:v} = \sum_{t=l+1}^{v} log(\epsilon_{i,t})$.

The monthly county-level returns R^c_t are estimated by the coefficients on monthly dummies in panel weighted least squares regressions. As in Robertson and Spiegel (2017), the weights are computed as the ratio between the squared root of bond issue amounts and the squared root of the time length between $l + 1$ and v so that larger issues and more recent trades are assigned larger weights. The returns in year y are estimated using years $y - 1$, y, and $y + 1$ in three-year rolling window regressions.[38] The results are reported in Table V and are consistent with the analysis in Table VIII.

V. Conclusion

This study highlights 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 investors price the value of natural capital only after the county experiences an extreme weather event. Next, I connect the mitigation premium to the loss of natural capital and the related increase in weather damages.

The results show that counties that destroy their natural capital experience a higher cost of debt after an extreme weather 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

[38] As highlighted by Auh et al. (2021) and Spiegel and Starks (2016), it is possible that multicollinearity arises when bonds do not trade in a county for consecutive weeks. To avoid this issue, I follow Auh et al. (2021) and merge the dummy variables into a single dummy and evenly split the estimated coefficients when multicollinearity occurs.

and revenue bonds 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. 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. Nevertheless, 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 contributes to the literature by identifying a mitigation premium in municipal bond markets and economically valuing the mitigating power of local natural capital against extreme weather events. Moreover, this paper is the first to introduce the implications of nature conservation in a finance context. 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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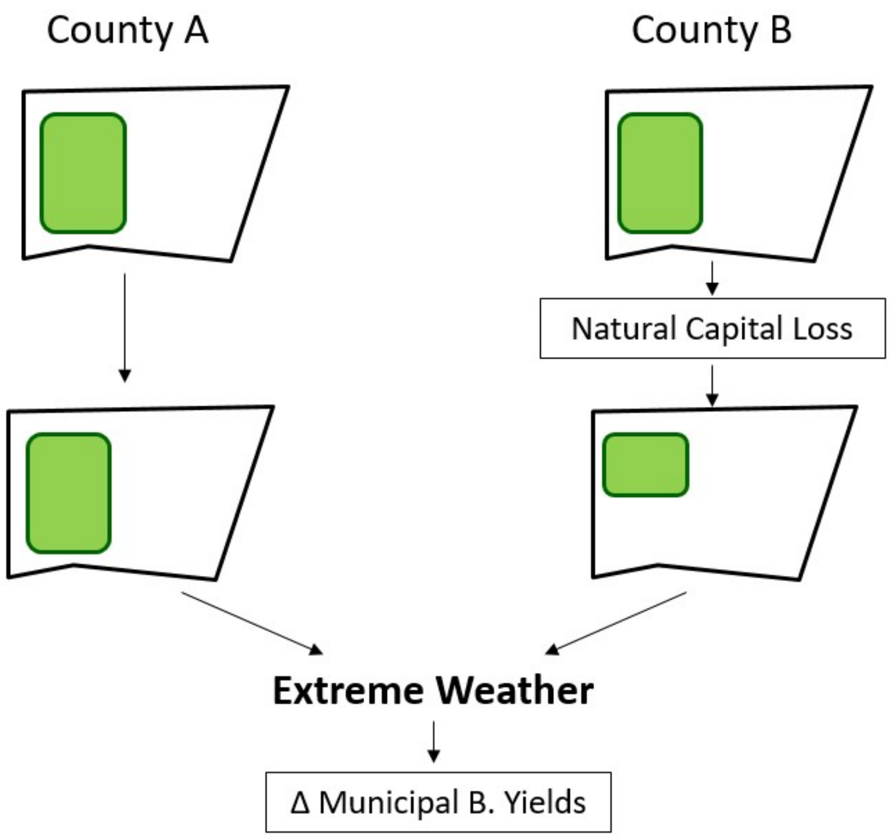

Figure 1: This figure represents the exemplification of the quasi-experiment utilized in the difference-in-difference analysis.

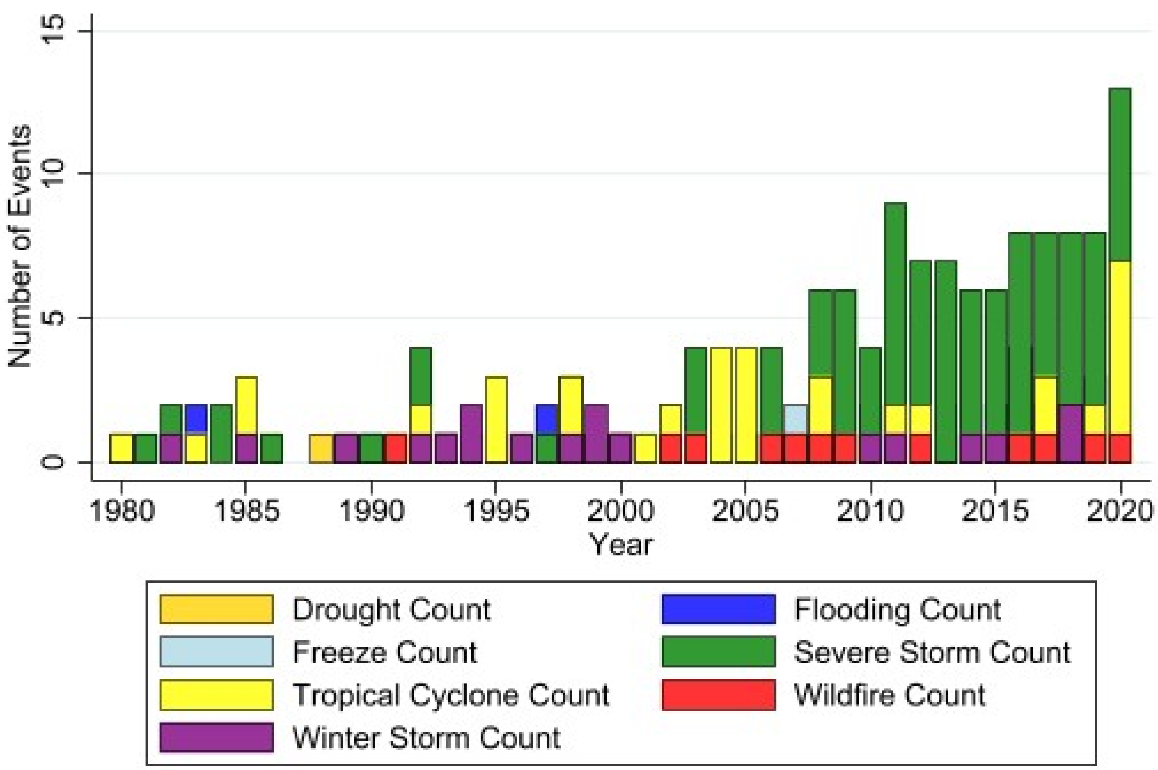

Figure 2: This graph reports the frequency of billion-dollar disaster events in the United States from 1980 to 2020 by type of disaster. The data was collected from the NOAA website.

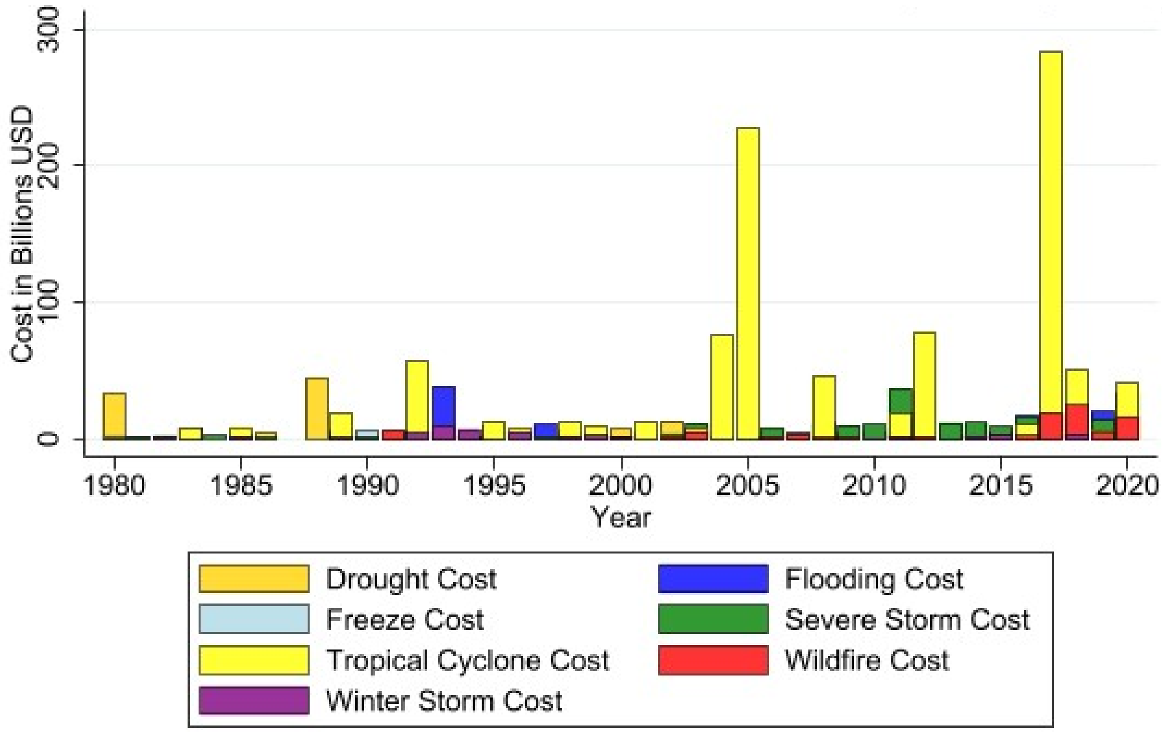

Figure 3: This graph reports the CPI-adjusted damages of billion-dollar disaster events in the United States from 1980 to 2020 by type of disaster. The data was collected from the NOAA website.

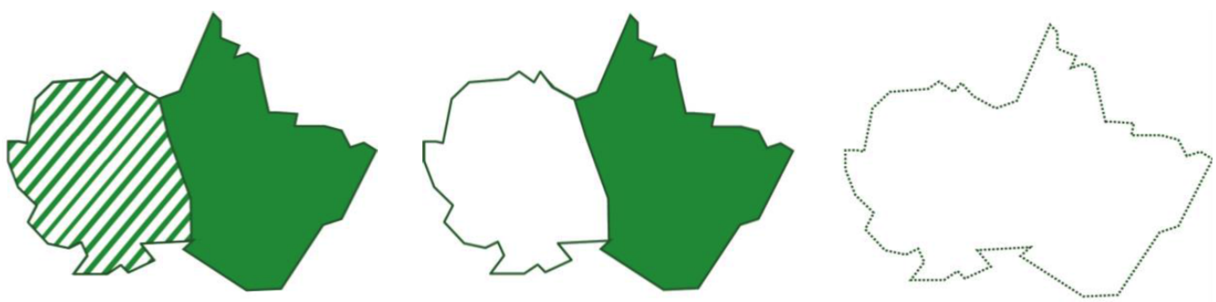

Figure 4: This figure represents the graphical representation of protected area downgrading, downsizing, and degazettement (PADDD) (Mascia et al. (2012)).

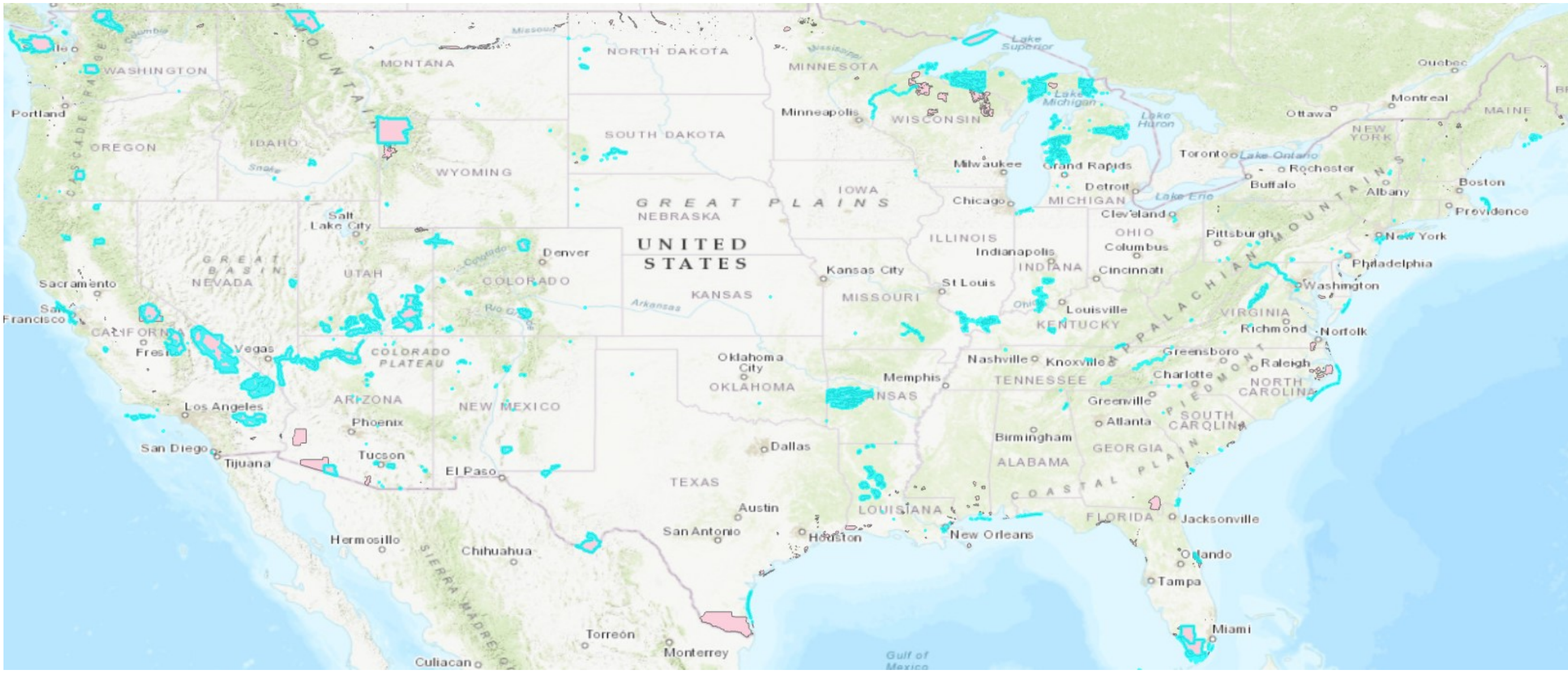

Figure 5: This figure represents the protected areas in the contiguous U.S. that experienced a PADDD event from 1976 to 2020.

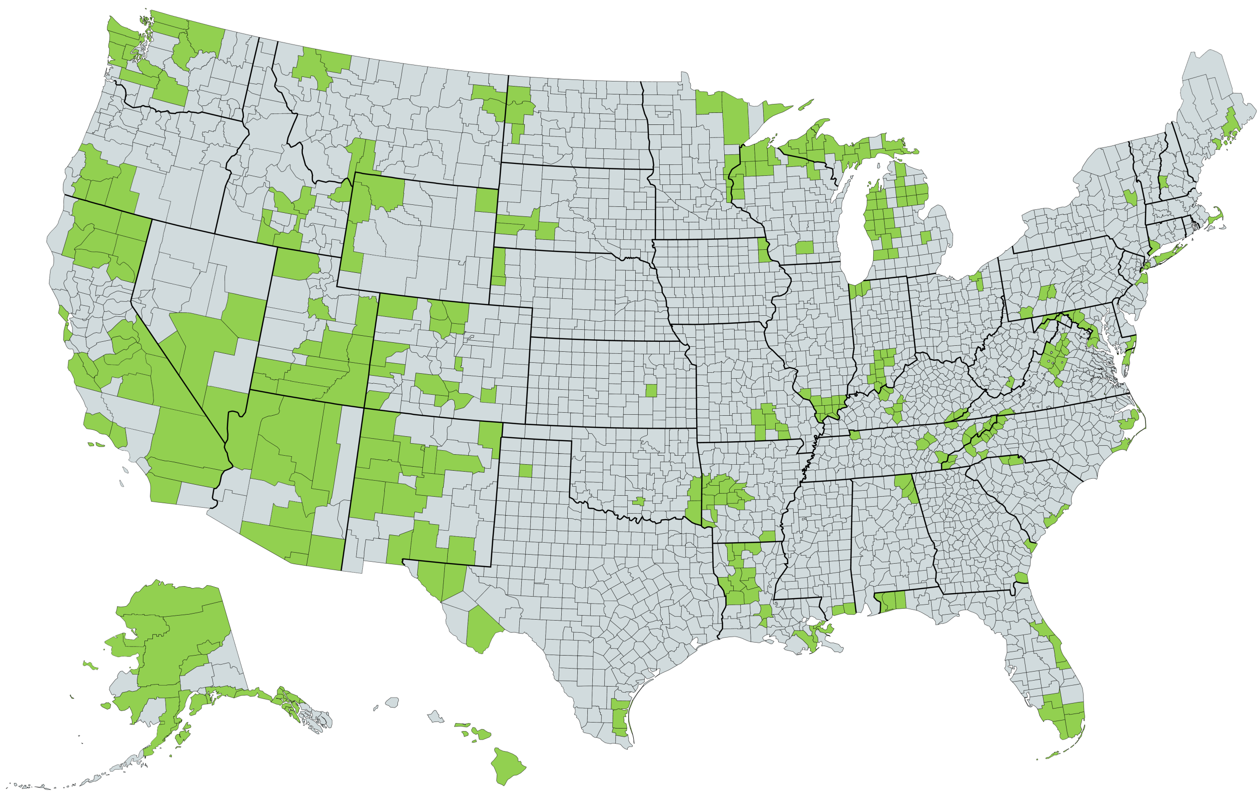

Figure 6: This figure represents the U.S. counties that experienced natural capital loss (i.e. PADDD) from 1976 to 2020.

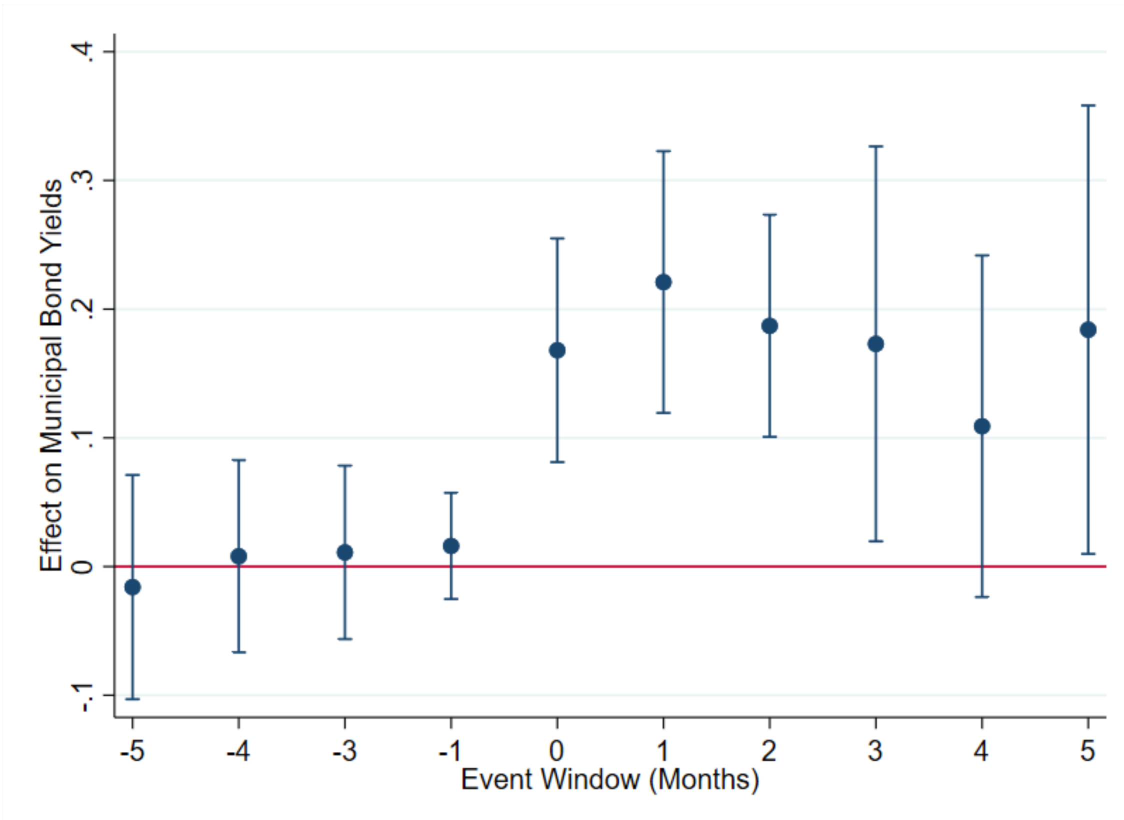

Figure 7: This figure represents the coefficients from the difference-in-difference regression of monthly county-level volume-weighted average municipal bond yields before and after an extreme weather event (Table VII column (2)). The vertical lines represent 95% confidence bands. The coefficients are estimated using month $t-2$ as reference. The controls include county characteristics (urban-rural classification, population, density, personal income, unemployment rate, ratio of protected area to total county area, proximity to the coast, elevation, quintile indicators for debt-to-tax-revenue ratio and revenue concentration, dichotomous indicator for FEMA transfers, and trend variables ($t-2$ to $t-1$) for population, density, personal income, and unemployment rate), municipal bond characteristics averaged at the county level (coupon rate, rating, years to maturity, years since issuance, size of the bond issue, and the ratio of trading volume to amount outstanding), and the intensity of the weather event. The specifications include state-year fixed effects. The standard errors are clustered at the state level.

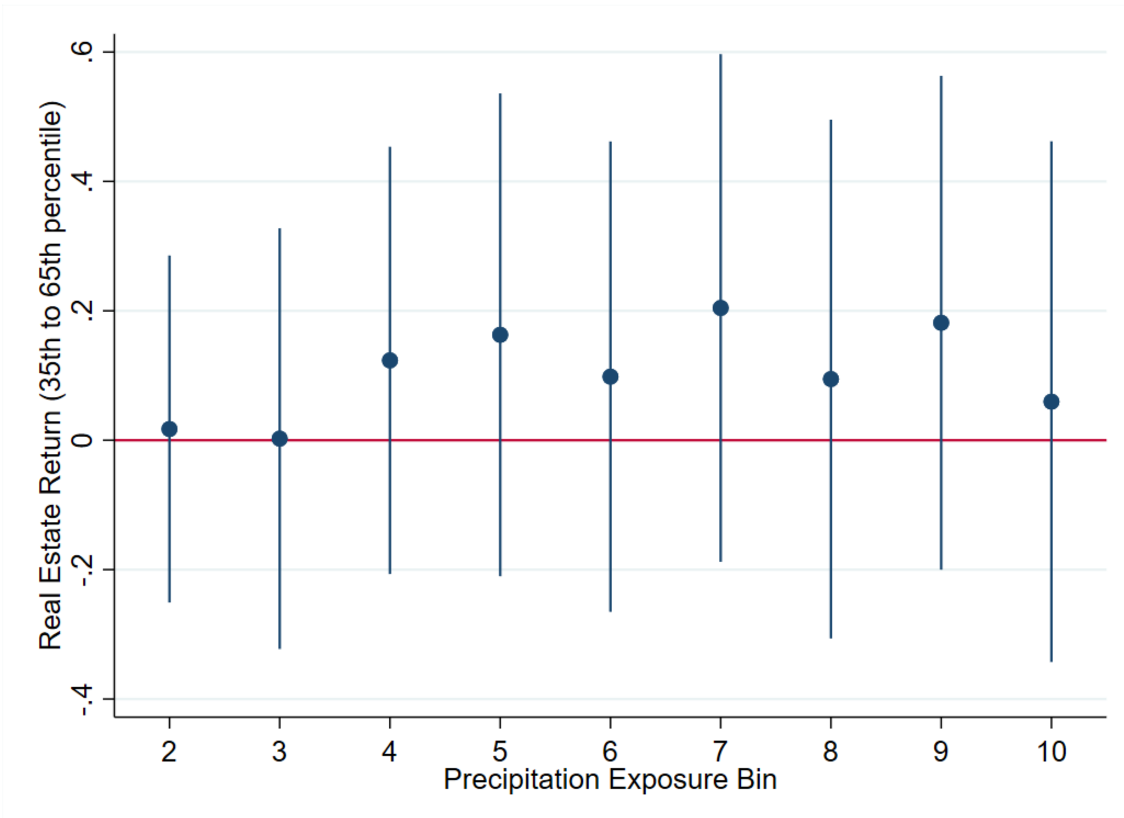

Figure 8: This figure represents coefficients from the semi-parametric regressions of real estate returns on precipitation exposure. The real estate return is calculated using the Zillow All Homes Time Series, Smoothed and Seasonally Adjusted for homes in the 35^{th} and 65^{th} percentile. Each county 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, population, density, personal income, unemployment rate, ratio of protected area to total county area, proximity to the coast, elevation, quintile indicators for debt-to-tax-revenue ratio and revenue concentration, dichotomous indicator for FEMA transfers, and trend variables ($t-2$ to $t-1$) for population, density, personal income, and unemployment rate. The regression specification includes state-year fixed effects and the standard errors are clustered at the state level.

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 US 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 1969 and ends in 2018.

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 by Urban-Rural Classification - 2005-2018 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 2018.

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 IV: PADDD Events by State - 2005-2018 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 2018.

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 V: 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 2005 and ends in 2018. The definitions of PADDD causes are listed in the appendix.

Cause of PADDD	Freq.	Percent	Area Affected (km^2)	Area Affected (mi^2)	% of Total Area Affected
Subsistence	235	75.1%	67,488	26,057	81.7%
Infrastructure	42	13.4%	5,383	2,078	6.5%
Land Claims	20	6.4%	3,679	1,421	4.5%
Oil and Gas	5	1.6%	29	11	0.0%
Mining	4	1.3%	3,803	1,468	4.6%
Other	7	2.2%	2,217	856	2.7%
Total	313	100%	82,599	31,892	100%

Table VI: 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.

Panel A: Bond Characteristics

	PADDD			No PADDD		
	Obs.	Mean	St.Dev.	Obs.	Mean	St. Dev.
Mun. Bond Yield (%)	21,244	3.04	1.17	714,775	3.02	1.10
Rating	21,244	4.52	1.81	714,775	4.86	1.63
Maturity Years since Issuance	21,244	14.71	7.73	714,775	15.43	7.07

Panel B: County Characteristics

	PADDD			No PADDD		
	Obs.	Mean	St.Dev.	Obs.	Mean	St. Dev.
Weather Damages ($M)	8,650	2.59	37.15	126,321	3.01	64.05
Weather Exp.	8,650	0.11	1.01	126,321	0.36	0.85
Population	8,650	60,521	109,514	126,321	44,985	81,882
Personal Income ($)	8,650	19,561	14,721	126,321	19,138	12,875
Unemployment (%)	8,650	6.12	2.81	126,321	6.98	3.01
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
FEMA Transfers ($M)	8,650	2.65	48.21	126,321	2.88	52.15
Debt/Tax Revenue	8,650	3.68	8.28	126,321	3.72	9.24
Housing Price Index (35^{th} to 75^{th})	2,767	221,474	166,856	51,791	145,764	113,227

Table VII. Natural Capital Loss and Bond Yields - Extreme Weather Events
This table reports the difference-in-difference estimation coefficients with monthly county-level volume-weighted average municipal bond yields as the dependent variable and extreme weather events as exogenous shock. The sample in column (1) includes all bonds. Instead, columns (2) and (3) include only revenue and general obligation bonds, respectively. The Treated variable indicates municipal bonds of counties that experienced a PADDD event no earlier than three years before the disaster. The controls include county characteristics (urban-rural classification, population, density, personal income, unemployment rate, ratio of protected area to total county area, proximity to the coast, elevation, quintile indicators for debt-to-tax-revenue ratio and revenue concentration, dichotomous indicator for FEMA transfers, and trend variables ($t-2$ to $t-1$) for population, density, personal income, and unemployment rate), municipal bond characteristics averaged at the county level (coupon rate, rating, years to maturity, years since issuance, size of the bond issue, and the ratio of trading volume to amount outstanding), and the intensity of the weather event. The specifications include 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)	−0.016	−0.016	−0.015
	(−0.36)	(−0.40)	(−0.37)
Treated × 1(Month -4)	0.008	−0.010	0.014
	(0.21)	(−0.25)	(0.21)
Treated × 1(Month -3)	0.011	0.052	0.009
	(0.32)	(0.76)	(0.15)
Treated × 1(Month -2)	-	-	-
	-	-	-
Treated × 1(Month -1)	0.016	0.018	0.015
	(0.76)	(0.31)	(0.30)
Treated × 1(Month 0)	0.168***	0.325***	0.142**
	(3.79)	(2.08)	(2.01)
Treated × 1(Month 1)	0.221***	0.481***	0.191**
	(4.26)	(4.96)	(2.15)
Treated × 1(Month 2)	0.187***	0.399**	0.185***
	(4.25)	(2.36)	(2.91)
Treated × 1(Month 3)	0.173**	0.251**	0.122*
	(2.21)	(2.08)	(1.88)
Treated × 1(Month 4)	0.109	0.136	0.113
	(1.61)	(1.69)	(1.54)
Treated × 1(Month 5)	0.184**	0.359***	0.133*
	(2.07)	(2.62)	(1.91)
Controls	Y	Y	Y
State-Year FE	Y	Y	Y
Observations	15,105	8,531	11,148

Table VIII. Natural Capital Loss and Bond Yields - Extreme Weather Event Intensity

This table reports the difference-in-difference estimation coefficients with monthly county-level average volume-weighted municipal bond yields as dependent variable and extreme weather events as exogenous shock. The sample in column (1) includes all bonds. Instead, columns (2) and (3) include only revenue and general obligation bonds, respectively. The Treated variable indicates municipal bonds of counties that experienced a PADDD event within three years before the weather event. $Weather\,Exp.$ represents the intensity of the extreme weather event. Post represents the time period after the extreme weather event. The controls include county characteristics (urban-rural classification, population, density, personal income, unemployment rate, ratio of protected area to total county area, proximity to the coast, elevation, quintile indicators for debt-to-tax-revenue ratio and revenue concentration, dichotomous indicator for FEMA transfers, and trend variables ($t-2$ to $t-1$) for population, density, personal income, and unemployment rate), municipal bond characteristics averaged at the county level (coupon rate, rating, years to maturity, years since issuance, size of the bond issue, and the ratio of trading volume to amount outstanding), and the intensity of the weather event. The specifications include 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	0.192***	0.395***	0.141**
	(3.32)	(3.11)	(2.12)
Treated × Weather Exp. × Post	0.181***	0.280***	0.137**
	(2.88)	(3.17)	(1.99)
Controls	Y	Y	Y
State-Year FE	Y	Y	Y
Observations	15105	8531	11148

Table IX: Natural Capital Loss and Annual Weather 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, $Weather\,Exp._{1-5}$, $Weather\,Exp._{6-10}$, quintile indicators for debt-to-tax-revenue ratio and revenue concentration, dichotomous indicator for FEMA transfers, 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 matching is performed using propensity score and restricting the matches to counties in the same state and with the same urban-rural classification. The variables utilized for the propensity score match are the following: county extreme weather exposure in the past five years, density, population, personal income, unemployment rate, tercile indicators for debt-to-tax-revenue ratio and revenue concentration, a dichotomous indicator for FEMA transfers, natural capital size (protected area), and trend in population. 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	9.71**	9.41**	23.75**
	(1.85)	(1.83)	(2.01)
$Weather\,Exp._{1-5}$	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	9,563

Table X: Natural Capital Loss and Bond Yields - Physical vs Non-physical Use of Proceeds

This table reports the difference-in-difference estimation coefficients using the bonds' use of proceeds and extreme weather as exogenous shock. The dependent variable is the monthly volume-weighted municipal bond yield. The Treated variable indicates municipal bonds of counties that experienced a PADDD event within three years before the weather event. Post is an indicator equal to one for observations occurring after the extreme weather event and zero otherwise. Physical indicates bonds with the use of proceeds classified as physical (see appendix for more details). The controls include county characteristics (urban-rural classification, population, density, personal income, unemployment rate, quintile indicators for debt-to-tax-revenue ratio and revenue concentration, dichotomous indicator for FEMA transfers, and trend variables ($t-2$ to $t-1$) for population, density, personal income, and unemployment rate), municipal bond characteristics (coupon rate, rating, years to maturity, years since issuance, size of the bond issue, and the ratio of trading volume to amount outstanding), and the intensity of the weather event. The specifications include county and state-year fixed effects. Column (1) reports the regression estimates and columns (2) and (3) report the matching estimates. For column (2), the matches are restricted to bonds issued in the same state with the same rating, type (general obligation or revenue), and county FEMA transfers indicator (i.e., below or above median FEMA transfers). I also allow a maximum of two year difference in maturity and a maximum of six months difference in the extreme weather event date. The variables used for the propensity score include $Weather\,Exp._{1-5}$, population, density, natural capital size (protected area), personal income, unemployment rate, debt-to-tax-revenue ratio, revenue concentration, trend in population, coupon rate. For column (3), I match bonds issued by the same county in the same year. 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	0.145**	0.217***	0.220***
	(2.32)	(3.18)	(3.51)
Treated × Post × Physical	0.140***	0.182***	0.241***
	(3.15)	(3.67)	(2.98)
Treated Bonds	4,852	651	143
Control Bonds	38,450	1,218	266
Physical Bonds	18,187	785	200
Non-Physical Bonds	25,115	1,084	209
County Controls	Y	Y	N
Bond Controls	Y	Y	Y
Fixed Effects	Y	-	-
Same County, same Year	N	N	Y
Observations	82,101	3,906	858

Table XI: Natural Capital Loss and Bond Yields - Neighboring Counties

This table reports the coefficients of the regression (column (1)) and the matching estimation (columns (1) and (2)). The dependent variable is the monthly county-level average volume-weighted municipal bond yield. The Treated variable indicates municipal bonds of counties that are within a 25-miles radius from a county that experienced a PADDD event within three years before the disaster. Post is an indicator equal to one for observations occurring after the extreme weather event and zero otherwise. The controls utilized for the regression estimation in column (1) include county characteristics (urban-rural classification, population, density, personal income, unemployment rate, quintile indicators for debt-to-tax-revenue ratio and revenue concentration, dichotomous indicator for FEMA transfers, and trend variables ($t-2$ to $t-1$) for population, density, personal income, and unemployment rate), municipal bond characteristics (coupon rate, rating, years to maturity, years since issuance, size of the bond issue, and the ratio of trading volume to amount outstanding), and the intensity of the weather event. The specification in column (1) includes county and state-year fixed effects. For columns (2), the matches are restricted to bonds issued in the same state with the same rating, type (general obligation or revenue), and county FEMA transfers indicator (i.e., below or above median FEMA transfers). I also allow a maximum of two years difference in maturity and a maximum of six months difference in the event date. The variables used for the propensity score include $Weather\,Exp._{1-5}$, population, density, natural capital size (protected area), personal income, unemployment rate, debt-to-tax-revenue ratio, revenue concentration, trend in population, coupon rate. For column (3), I match bonds issued by the same county in the same year. 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	0.185**	0.148***	0.166***
	(2.01)	(3.41)	(3.55)
Treated × Post × Physical	0.175***	0.325***	0.373***
	(3.18)	(4.16)	(4.71)
Treated Bonds	8,491	823	178
Control Bonds	34,632	1,563	341
Physical Bonds	18,974	1,098	223
Non-Physical Bonds	24,149	1,288	296
County Controls	Y	Y	N
Bond Controls	Y	Y	Y
Same County, Same year	N	N	Y
Fixed Effects	Y	-	-
Observations	95,523	4,938	1,068

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

This table reports the difference-in-difference estimation coefficients with monthly county-level average volume-weighted municipal bond yields, personal income, and population as dependent variables. The analysis in column (1) uses extreme weather events as exogenous shock. Instead, the rest of the analysis is performed using PADDD as exogenous shock. For column (1), the Treated variable indicates counties that experienced a PADDD event (or are within a 25-miles radius) within three years before the extreme weather event. For columns (2) and (3), the Treated variable indicates counties that experienced a PADDD event or are within a 25-miles radius. The farming indicator equals one if the county is classified as economically dependent on farming by the BEA. For column (1) ((2) and (3)), the Post is an indicator equal to one for observations occurring after the extreme weather event (natural capital loss event) and zero otherwise. The controls utilized for the regression estimation in column (1) include county characteristics (urban-rural classification, population, density, personal income, unemployment rate, ratio of protected area to total county area, proximity to the coast, elevation, quintile indicators for debt-to-tax-revenue ratio and revenue concentration, dichotomous indicator for FEMA transfers, and trend variables ($t-2$ to $t-1$) for population, density, personal income, and unemployment rate), municipal bond characteristics averaged at the county level (coupon rate, rating, years to maturity, years since issuance, size of the bond issue, and the ratio of trading volume to amount outstanding), and the intensity of the weather event. Columns (2) and (3) do not include bond controls. The specifications in column (1) include state-year fixed effects. The specifications in columns (2) and (3) 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	0.152***	−0.058	−0.13*
	(3.53)	(−0.82)	(−1.91)
Treated × Post × Farming	0.171***	−0.338**	−0.15
	(4.13)	(−2.82)	(−1.56)
County Controls	Y	Y	Y
Bond Controls	Y	-	-
Fixed Effects	Y	Y	Y
Observations	17,221	170,293	170,293

Table XIII. Natural Capital Loss and Bond Yields - Placebo Test

This table reports the difference-in-difference estimation coefficients with monthly county-level average volume-weighted municipal bond yields as dependent variable and extreme weather events as exogenous shock. The sample in column (1) includes all bonds. Instead, columns (2) and (3) include only revenue and general obligation bonds, respectively. 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. Post represents the time period after the extreme weather event. The controls include county characteristics (urban-rural classification, population, density, personal income, unemployment rate, ratio of protected area to total county area, proximity to the coast, elevation, quintile indicators for debt-to-tax-revenue ratio and revenue concentration, dichotomous indicator for FEMA transfers, and trend variables ($t-2$ to $t-1$) for population, density, personal income, and unemployment rate), municipal bond characteristics averaged at the county level (coupon rate, rating, years to maturity, years since issuance, size of the bond issue, and the ratio of trading volume to amount outstanding), and the intensity of the weather event. The specifications include 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	0.008	0.036	0.013
	(0.46)	(0.31)	(0.18)
Controls	Y	Y	Y
State-Year FE	Y	Y	Y
Observations	15,105	8,531	11,148

Table XIV. Natural Capital Loss and Bond Yields - Repeated Sales

This table reports the difference-in-difference estimation coefficients with monthly county-level municipal bond returns computed using the repeated sales method as dependent variable and extreme weather events as exogenous shock. The sample in column (1) includes all bonds. Instead, columns (2) and (3) include only revenue and general obligation bonds, respectively. 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. Post represents the time period after the extreme weather event. The controls include county characteristics (urban-rural classification, population, density, personal income, unemployment rate, ratio of protected area to total county area, proximity to the coast, elevation, quintile indicators for debt-to-tax-revenue ratio and revenue concentration, dichotomous indicator for FEMA transfers, and trend variables ($t-2$ to $t-1$) for population, density, personal income, and unemployment rate), municipal bond characteristics averaged at the county level (coupon rate, rating, years to maturity, years since issuance, size of the bond issue, and the ratio of trading volume to amount outstanding), and the intensity of the weather event. The specifications include 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	0.215***	0.381***	0.167**
	(3.51)	(3.47)	(2.17)
Treated × Weather Exp. × Post	0.174***	0.261***	0.148**
	(2.91)	(3.31)	(2.03)
Controls	Y	Y	Y
State-Year FE	Y	Y	Y
Observations	15,817	8,913	11,842