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

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Abstract

This paper shows that natural capital loss affects financial markets and municipalities' borrowing costs. Using exogenous variation in wetlands change, I find that a loss in wetland area is related to an increase in municipal bond yields in both primary and secondary markets. Municipal bond markets price nature loss risk following an extreme precipitation event. The effect is more prominent for bonds issued by counties more reliant on local tax revenue, farming communities, revenue bonds, and bonds financing infrastructure projects. The results show one of the costs of natural capital destruction on financial markets and local government's finances.

Keywords: Climate change, nature valuation, municipal debt, wetlands.
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"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.

Global warming has and will have serious implications for economies worldwide and the financial system. Hence, scholars have focused on understanding how and if climate change risk is internalized by financial markets. However, another strictly related issue has not received much attention from finance scholars: nature and biodiversity loss (Karolyi and Tobin-de la Puente (2023)). Natural areas such as wetlands and forests are extremely effective in mitigating the damages of extreme weather events as well as climate change risk. Estimating how nature loss affects financial markets is essential when assessing the overall costs and benefits of nature conservation.

In this study, I examine whether nature or natural capital loss risk is priced in financial markets and whether nature loss affects local borrowing costs. Municipal bonds provide an ideal setting for studying this question since investors need to account for local risks when pricing these assets. As opposed to firms, municipalities cannot move to avoid extreme weather and other effects related to climate change and need to rely on adaptation strategies. This local risk affects the municipality's tax revenue, cash flow volatility, and the likelihood that it can repay the bonds issued. For this reason, I can use the municipal bond market to infer if natural capital loss risk is priced in financial markets and estimate the value of nature conservation.

Quantifying how natural capital conservation affects financial markets is difficult for a few reasons.[1] 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 address these issues, I identify the causal effect of long-term loss of natural capital on municipal bond yields

[1]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.

using exogenous variation in wetlands. Specifically, I utilize the long differences (LD) and the upstream-downstream difference-in-differences (DID) approaches proposed by Taylor and Druckenmiller (2022).

Among many other ecosystem services, wetlands provide flood mitigation absorbing excess precipitation during rainfall. However, the presence of wetlands is associated with other factors that influence flood damage, such as wetter climates. In addition, when wetlands are lost to development, the area loses protection from flooding but also experiences an increase in physical capital at risk. Comparing wetland area changes upstream versus downstream of the county using the upstream-downstream DID approach allows disentangling the two effects since only upstream wetlands mitigate flood damage.

I find that wetland loss increases municipal bond yields and borrowing costs. In particular, a one standard deviation loss in upstream wetlands (748 hectares or 2.2 times the size of Central Park in New York City) results in an increase of 0.47% in bond yields and $4 million in annual borrowing costs for an average county. This is equivalent to 11% of annual interest expense on bonds outstanding. In addition, bondholders experience a loss in wealth of about $6.3 billion.

The channels that link municipal bond yields to wetland loss are related to extreme weather risk and local revenue risk. Specifically, consistent with the findings in Taylor and Druckenmiller (2022), I find that a one-hectare loss in upstream wetlands is related to an increase between $13,621 and $15,792 in weather damages. This result emphasizes how nature conservation directly decreases local extreme weather risk. In addition, counties more dependent on local revenue experience the largest yield increases, providing evidence of a direct link between natural capital loss and the local cash flows available to repay bonds. I also find that months with heavy precipitation events, wetlands converted into development, and farming communities display the highest yield increase.

To provide further insights on the pricing of natural capital loss risk, I employ a novel quasi-experiment setup that exploits local extreme weather shocks and natural capital loss events. The quasi-experiment 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 (Figure 1). The extreme weather event is selected using a physical and exogenous measure of weather: precipitation. Then, I estimate the difference in bond yields between the two counties by computing the county-level volume-weighted average bond yields.

I find no difference in bond yields after the natural capital loss event. However, the results show that, after an extreme weather event, the yield spread between counties that experience a natural capital loss and those that do not, i.e., "nature premium", increases from zero to an average of 17 basis points (5.6% of average yield). This increase in yields in the secondary market reflects the higher extreme weather risk of areas affected by natural capital loss. The loss of disaster mitigation results in a reduction of bondholders' wealth of about $2.45 billion. Regarding the primary market, an average county experiences an increase of 5.6 basis points in offering yields, which equates to an increase in borrowing costs of about $0.7 million or 2% of a county's annual interest expense on bonds.

The positive yield impact occurs mostly for revenue bonds, but the effect is also economically and statistically significant for general obligation (GO) bonds. This difference in impact could be due to the distinct nature of the bonds' cash flows. Specifically, revenue bonds are supported by the revenue from the specific government project and GO bonds are backed by overall municipal tax revenue. Further, the nature premium does not disappear shortly after the extreme weather event. In particular, I find evidence of its persistence for up to three years after the extreme weather event for yields in the primary and secondary market, as well as credit ratings. Also, the effect of natural capital loss is positively related to the strength of the weather events and affects neighboring counties almost as strongly as counties that lose the natural capital. Bonds used to fund infrastructure projects display a higher yield increase than bonds with other use of proceeds (e.g., cash flow management and repayment of bank loans). The nature premium is higher after 2012 and for bonds with longer maturities, and it is not affected by the local political and climate change beliefs.

Collectively, this study shows that natural capital is an important determinant of municipal bond pricing due to its direct impact on extreme weather and climate change risk. Investors become aware of the relation between nature and local risk after an extreme weather event and this is reflected in the differences in municipal bond yields. Using the upstream-dowstream DID, I am also able to approximate the value of natural capital using a market-based forward-looking estimate.

This paper is the first to examine the impact of nature loss on financial markets. Hence, I build upon studies in environmental economics such as Narayan et al. (2017) and Taylor and Druckenmiller (2022) and explore the financial implications of nature loss for counties focusing on municipal bond markets and borrowing costs.[2] Specifically, Narayan et al. (2017) examines the role of coastal wetlands in avoiding damage during hurricanes. Also, Taylor and Druckenmiller (2022) causally identify the impact of wetland loss on flood insurance claims. Collectively, this literature highlights the critical role of nature in mitigating the effects of natural disasters.

In addition, this work contributes to the literature studying the local conditions affecting municipal bond yields (Gao, Lee, and Murphy (2019), Gao, Lee, and Murphy (2020), Dougal et al. (2019), and Chava, Malakar, and Singh (2019)). In particular, these results are in line with the Goldsmith-Pinkham et al. (2021) study, which shows that exposure to sea-level rise (SLR) increases municipal bond yield spreads. The study shows that the pricing of SLR risk began in 2013. This effect might be due to the more extensive media attention and the multiple extreme weather events experienced during these years. Also, Painter (2020) finds that counties more likely to be exposed to climate change report higher initial yields for municipal bonds with long maturities. My work differs from the previous literature by analyzing the role of nature loss on municipal bonds instead of the role of climate change risk.

In another related study, Auh et al. (2021) analyze the effect of natural disasters on municipal bonds. In particular, they utilize the repeated sales approach to overcome the lack of bond transactions at a high enough frequency. They show that counties hit by natural disasters experience lower bond returns. My paper complements these insights by examining the implications of nature loss for counties facing natural disaster risk.[3]

[2] Other related studies include Costanza et al. (2008), Sudmeier-Rieux, Ash, and Murti (2013), Murti and Buyck (2014), Da Silva and Wheeler (2017), Johnson et al. (2020), and Sun and Carson (2020).

[3] Other studies that examine the effect of natural disasters and environmental regulations on municipal bonds include Fowles, Liu, and Mamaril (2009), Bourdeau-Brien and Kryzanowski (2019), and Jha, Karolyi, and Muller (2020).

In a recent study, Hong, Wang, and Yang (2020) develop a theoretical model that describes the relation between costly mitigation to disaster risks, beliefs regarding the consequences of global warming, and the impact on capital stock. 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 disaster risk mitigation expenditure. My analysis integrates the theoretical intuition in Hong, Wang, and Yang (2020) with an empirical estimation of the impact of one specific disaster mitigation infrastructure, wetlands, on municipal bonds.

The results reported in this paper also complement the growing literature on financial assets and climate risk. These studies examine the relation between climate-related risks and the cost of capital (Sharfman and Fernando (2008), Chava (2014), and Delis, Greiff, and Ongena (2019)), firm valuation (Bansal, Kiku, and Ochoa (2016), Berkman, Jona, and Soderstrom (2019), Hong, Li, and Xu (2019)), operating performance (Barrot and Sauvagnat (2016) and Addoum, Ng, and Ortiz-Bobea (2020)), corporate policies (Dessaint and Matray (2017)), and corporate bond returns (Huynh and Xia (2021)).

Another strand of the literature shows how climate risk affects the allocation of credit by banks (e.g., Cortés and Strahan (2017) and Brown, Gustafson, and Ivanov (2020)), mortgage markets (Sastry (2021)), real estate (Baldauf, Garlappi, and Yannelis (2020) and Bernstein, Gustafson, and Lewis (2019)), insurance claims (Taylor and Druckenmiller (2022)), and the beliefs of institutional investors (Krueger, Sautner, and Starks (2020)). Giglio, Maggiori, and Stroebel (2015) and Giglio, Maggiori, Rao, et al. (2021) examine the appropriate discount rates to be used to discount the long-run risks of climate change. In addition, Baker et al. (2018), Larcker and Watts (2020), and Flammer (2021) provide insights on the pricing of "green" bonds. Lastly, Bruno and Henisz (2022) and Lu and Nakhmurina (2022) highlight the role of adaptation and ESG factors in municipal bond markets. I contribute to this literature by analyzing the role of nature loss risk and the value of natural capital in protecting local economies from negative shocks related to natural disasters.

More broadly, this paper is related to studies in economics that identified the implications of natural disasters. For example, a recent study by Jerch, Kahn, and Lin (2023) 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 local cost of debt. Moreover, these losses are found to be persistent for at least ten years after a hurricane strike. However, there is no consensus on the long-term effects of natural disasters, which might range from severely negative to positive (e.g., Deryugina, Kawano, and Levitt (2018) and Deryugina (2017)). In addition, Jia, Ma, and Xie (2022) show that increased flood risk negatively impacts local firm entry, employment, and output in the long term. I contribute to this discussion by examining the role of nature conservation and the implications for the local cost of capital.

The remainder of the paper is organized as follows. Section I offers some empirical and anecdotal evidence related to the importance of nature conservation. Section II provides a description of the data and summary statistics. Section III and IV present the empirical approach, results, and additional tests. I conclude in Section V with a brief summary.

I. Background and Motivation

A. Importance of Nature Conservation

Natural areas provide innumerable ecosystem services such as extreme weather mitigation, climate change adaptation, water quality improvement, and biodiversity conservation. Wetlands and forests collect excess precipitation acting as sponges and mitigating flood damages. These properties of wetlands have been shown to influence the peak flows, volume, timing, and duration of floods (Acreman and Holden (2013) and Thomas and Nisbet (2007)). Also, mangrove forests protect coastal areas from high wind speeds and storm surges during severe storms.

The environmental economics literature has highlighted the importance of nature conservation and its direct impact on weather damage mitigation. For instance, Narayan et al. (2017) show that coastal wetlands were able to avoid about $625 million in direct flood damage during Hurricane Sandy. Johnson et al. (2020) find that the avoided damages from future floods exceed the cost of acquisition and conservation of natural land by a factor of at least five to one.

Also, Taylor and Druckenmiller (2022) estimate the value of wetlands for flood mitigation using flood insurance claims and show that the average cost per hectare to society equals $1,840 annually and over $8,000 in developed areas. In addition, they find that the flood mitigation benefits of wetlands are the greatest during anomalously high precipitation events, which are projected to become more frequent with climate change.

Governments have started to implement nature-based solutions to mitigate the damage of extreme weather events. For instance, in recent years, Iowa started to experience floods like never before in its history, and Iowans endured the consequences of climate change first-hand. 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 to protect essential wildlife habitats, reduce water pollution, shield communities, businesses, and farmlands from floods, and protect fertile soil. This $150 million fund is expected to generate enormous societal, economic, and environmental benefits for Iowans (Tercek and Adams (2013)).

II. Data and Summary Statistics

A. Municipal Bond Data

The municipal bond data is collected from the Municipal Securities Rulemaking Board (MSRB). This dataset contains all municipal bond transactions from 2005 to 2020. The variables utilized in this study are the bond yield, coupon rate, years to maturity, size of the issue, and trade volume. Similar to Gao, Lee, and Murphy (2019), I include only customer buy transactions to eliminate time series variation due to the bid-ask bounce. Following Schwert (2017), I utilize only fixed-coupon and tax-exempt bonds that trade at least ten times.[4] 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

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

periods (Green, Hollifield, and Schürhoff (2007) and Schultz (2012)). To remove complications with embedded options, I remove callable bonds.[5] I complement the data from MSRB with information on bond characteristics from Bloomberg. Specifically, I collect the issuer name, county of issuance, offering yield, sources of funds, general obligation (GO) indicator, use of proceeds, credit rating, insurance status, and pre-refunding status and timing. I hand-collect the county affiliated with each bond if this information is missing.

For the credit rating, I convert the rating scale to a numeric classification as in Cantor and Packer (1997). For example, AAA (Moody's) and Aaa (Fitch and S&P) 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 "infrastructure" if the use of proceeds mentions a specific infrastructure project (Table IAI in the Internet Appendix). For example, a bond issue that mentions as use of proceeds "water utility" or "highway" will be classified as "infrastructure." On the other hand, a bond that cites as use of proceeds "student loans" or "lawsuit" will be classified as "non-infrastructure." This classification helps exploit the cross-sectional heterogeneity in the bonds' use of proceeds and the within-county heterogeneity in disaster exposure.

The transaction data from the MSRB, together with the information from Bloomberg, allow me to construct a monthly panel of volume-weighted yields at the bond and county level. The final sample contains 702,561 bonds for 2,013 counties.

B. Wetlands

I collect information on wetland changes from 2006 to 2016 following the approach in Taylor and Druckenmiller (2022). The information on the spatial extent of wetlands is collected from the National Land Cover Database (NLCD) (Dewitz (2021)).[6] This dataset includes remotely-sensed information on land cover across the United States. In 2006 and 2016, the NLCD reported that

[5]The results are qualitatively similar when including callable bonds. Following Green, Li, and Schürhoff (2010), I clean the data from obvious data errors. I eliminate all observations for a bond if the coupon and maturity are missing for all observations. I remove observations with the coupon recorded as greater than 20%, or if the maturity is recorded as over 100 years. I exclude all transactions where the price is less than 50% of face value. Lastly, I remove trades recorded after the maturity date.

[6]The latest data release contains land cover information from 2001 to 2016. Due to the limited land cover information and municipal bond data availability, I use the time period from 2006 to 2016 for the analysis.

wetlands cover a total of approximately 47.1 million hectares (5.8% of the contiguous U.S.). Figure 2 Panel A reports the geographical distribution of wetlands. Specifically, the blue scale represents the percentage of area covered by wetlands. In Figure 2 Panel B, the green and brown indicate gains and losses in wetlands between 2006 and 2016.

The NLCD is complemented with data on the U.S. water drainage network from the National Hydrography Dataset (NHD) (U.S. Geological Survey (2021)). This dataset is used to identify upstream and downstream wetlands for each county according to the flow direction in NHD's Watershed Boundary Dataset (WBD).[7] Table I Panel A reports the summary statistics for wetland area and change from 2006 to 2016.

C. County Economic and Political Data

The county-level economic and population data are collected from the U.S. Bureau of Economic Analysis (BEA) and the U.S. Bureau of Labor Statistics (BLS). For this study, I utilize county-level population, personal income, and unemployment rate from 1969 to 2020. I supplement the county's economic information with financial information from the Census of Governments, which reports local government debt, cash and securities, and tax revenue. I measure the revenue ratio based on the sources of general revenue of the local governments, which mainly include intergovernmental (IG) revenue from the federal government, IG revenue from the state government, and local revenue.

I collect information on the number of housing units and the median home value from the U.S. Census (U.S. Census Bureau (2000)) and the American Community Survey (U.S. Census Bureau (2016)). Lastly, I collect the county's elevation and distance from the coast based on its centroid coordinates. Following the National Center for Health Statistics (NCHS), I classify counties into six urban-rural categories: large central metropolitan areas, large fringe metropolitan areas, medium metropolitan areas, small metropolitan areas, micropolitan areas, and noncore.

[7]A watershed is an area of land that drains rainfall and snowmelt into streams and rivers. I am grateful to Dr. Taylor and Dr. Druckenmiller for allowing me to access and use the wetlands data from their paper Taylor and Druckenmiller (2022).

D. Weather Damages

I use the crop and property weather damage (in U.S. dollars) information from the National Oceanic and Atmospheric Administration (NOAA) for the 1969-2020 period. During this time period, a large portion of the damage is caused by events characterized by heavy precipitation (tropical cyclones, severe storms, and flooding). The states that experience the largest damages (in dollar terms) are Texas, Florida, and Louisiana.

E. Precipitation Data

I collect daily precipitation data from the Parameter-elevation Regressions on Independent Slopes Model or PRISM (PRISM Climate Group (2014)).[8] The dataset comprises total precipitation on a 2.5×2.5-mile grid for the contiguous United States from 1950 to 2020. I use the precipitation data because some of the most frequent and damaging extreme weather events in the past decades in the U.S. have been severe storms and tropical cyclones (Smith and Katz (2013)). Those weather events involve ample precipitation, which causes, together with storm surges in coastal areas, flooding. A portion of the damage from these events is caused by high winds. However, strong winds and heavy precipitation usually come together during these weather events.

In addition, as mentioned above, 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. Lastly, scholars have highlighted how a warming climate will bring more extreme precipitation.[9] Hence, these events and the related role of nature are becoming even more relevant and might affect financial markets and municipalities' borrowing costs.

[8]The full sample dataset from 1895 to present is publicly available on the following website `https://www.prism.oregonstate.edu/`. The sample period from 1950 to 2019 is available on Dr. Wolfram Schlenker's website (`http://www.columbia.edu/~ws2162/links.html`).

[9]See Hennessy, Gregory, and Mitchell (1997), Allen and Ingram (2002), Balling and Goodrich (2011), and Wu, Christidis, and Stott (2013).

F. Protected Area Downgrading, Downsizing, and Degazettement

To clarify the timing of nature loss pricing and provide robustness to the baseline results, I utilize the Protected Area Downgrading, Downsizing, and Degazettement (PADDD) data collected by the Conservation International and the World Wildlife Fund (WWF).[10] Downgrading is a decrease in legal restrictions on the number, magnitude, or extent of human activities within a PA. Downsizing is a decrease in the size of a PA as a result of the excision of an area of land or sea area through a legal boundary change. Lastly, degazettement is a loss of legal protection for an entire PA (Mascia and Pailler (2011)). The PADDD dataset contains more than 4,400 enacted PADDD events affecting an area nearly the size of India across 74 countries from 1892 to 2020 (Conservation International and World Wildlife Fund (2021)).

These data allow identifying the counties that experience a loss in natural capital. The dataset provides 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 2020. I include only wetlands and forests and exclude deserts and battlefields since they do not provide direct precipitation mitigation. I restrict the study to the U.S. since the drivers of PADDD across countries might be different and might be influenced by differences in legal framework, economic and political environment, as well as other observable and unobservable circumstances.

This dataset also includes the reported cause of PADDD. Panel C of Table II highlights how the cause of the majority of PADDD is characterized as subsistence.[11] The rest of the events are caused by infrastructure projects, mining, oil and gas extraction, land claims, or other unspecified reasons. I discuss summary statistics and the exogeneity of PADDD events in Section III.E.1.

[10] The dataset is available on `https://www.padddtracker.org`. See Mascia, Sharon, and Roopa (2012) and Conservation International and World Wildlife Fund (2021) for further details.

[11] The definitions for all causes of PADDD is reported in Table IAII of the Internet Appendix.

G. FEMA Federal Disaster Aids

I collect data on federal disaster aid to households and local governments from the Federal Emergency Management Agency (FEMA). I utilize the information on presidential disaster declaration to identify the annual disaster aid received by the county. Counties included in a presidential disaster declaration are eligible for public assistance, individual assistance, and/or hazard mitigation grants. I aggregate the information from all three programs and compile a measure of county-year federal disaster transfers similar to Auh et al. (2021) (FEMA Transfers). Next, I classify the sample into two groups, below-median and above-median FEMA transfers, creating a dichotomous variable. Table I contains the summary statistics of the variables used in this paper.

III. Empirical Approach

A. Identification Strategy

Wetland areas play a crucial role in mitigating flood risk because they can collect excess water during periods of extreme precipitation. However, the sole presence of wetlands cannot be used to capture the causal effect of nature loss on municipal bonds due to endogeneity concerns. For instance, areas with wetter climates have more wetlands and experience more intense and frequent extreme precipitation events.[12]

Hence, similar to Taylor and Druckenmiller (2022), to identify the causal relation between wetland loss and municipal bond yields, I utilize two identification strategies: long differences (LD) and upstream-downstream difference-in-differences (DID). The long differences highlight the long-term effect of local wetland changes on municipal bond yields in the secondary and primary markets accounting for time-invariant county characteristics. Specifically, I utilize the following LD model.

$$\Delta Y_{cs} = \beta \Delta W_{cs} + \lambda' \Delta X_{cs} + \delta_s + \epsilon_{cs}. \tag{1}$$

[12]As highlighted in Taylor and Druckenmiller (2022), the correlation between wetlands and flood damages is not evidence that wetlands cause weather damage due to confounding factors such as precipitation.

To avoid concerns related to year-specific effects, I compute volume-weighted average yields using observations from 2005 to 2006 and from 2015 to 2016. Then, I compute the difference between these two averages and use this difference as the main dependent variable, ΔY_{cs}.[13]

The vector of control variables X includes changes from 2006 to 2016 in county characteristics (population, density, income per capita, unemployment rate, housing value, developed area, National Flood Insurance Program (NFIP) Community Rating System, debt-to-tax-revenue ratio, local revenue ratio, and FEMA transfers), 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 precipitation.[14] The specifications include state fixed effects and the standard errors are clustered at the county level.

In additional tests, I allow for gains and losses to affect the dependent variables differently using the following model.

$$\Delta Y_{cs} = \beta_1 \Delta W_{cs}^{GAIN} + \beta_2 \Delta W_{cs}^{LOSS} + \lambda' \Delta X_{cs} + \delta_s + \epsilon_{cs}, \tag{2}$$

where W_{cs}^{GAIN} (W_{cs}^{LOSS}) represents the gain (loss) in wetland area in county c.

The second approach, i.e., the upstream-downstream DID, leverages the fact that flood risk should be affected by changes in upstream wetlands and not by changes in downstream wetlands. This is not the case for coastal counties, and, for this reason, these counties are excluded from the analysis. The main assumption for identification is that real estate development is not systematically biased toward either upstream or downstream areas relative to a given county. This assumption is tested in Taylor and Druckenmiller (2022). They show that there is no significant difference between upstream and downstream development. I replicate this analysis and find identical results.[15]

Hence, the DID estimator allows me to identify the disaster mitigation value of nature by

[13]The results are robust when using the change in bond yields between 2006 and 2016.

[14]The NFIP Community Rating System reflects a community attitude to flood risk. Participation in the program provides discounted flood insurance premiums reflecting the community's efforts to mitigate flood risk.

[15]Also, I find that upstream wetlands change is not related to changes in population, income per capita, unemployment rate, and local revenue over the sample period.

exploiting the different effects of wetlands changes upstream versus downstream. The DID model is provided below.

$$\Delta Y_{cs} = \beta_1 \Delta W_{cs} + \beta_2 \Delta W_{cs}^{UP} + \beta_3 \Delta W_{cs}^{ALL} + \lambda' \Delta X_{cs} + \delta_s + \epsilon_{cs}, \tag{3}$$

where W_{cs} represents changes in wetland area in county c. W_{cs}^{UP} represents changes in wetland area upstream of county c. W_{cs}^{ALL} represents changes in wetland area both upstream and downstream of county c. The coefficient of interest is β_2.

B. Baseline Estimates

Table III reports the results of the long differences and upstream-downstream difference-in-differences. The dependent variables are the county-level volume-weighted average municipal bond yields in the secondary (columns (1)-(4)) and primary markets (columns (5)-(8)). The results show that a loss in wetlands increases bond yields. Specifically, in the secondary market, the long difference estimates show that a one standard deviation loss in local wetlands (655 hectares) results in an increase of 0.26% (0.039 b.p $\times$ 655) in yields over eleven years, i.e., 8.5% of the average yield.

The upstream-downstream DID estimates isolate the causal effect of wetlands loss on municipal bond yields. In particular, columns (2) and (4) show that a one standard deviation increase in upstream wetlands (748 hectares) results in an increase in bond yields of 0.47% (0.063 $\times$ 748; 15% of the mean yield). The results for offering yields in columns (5)-(8) are qualitatively similar. Note that the gain in wetlands does not affect municipal bond yields. In comparison, Auh et al. (2021) find that natural disasters decrease municipal bond returns by between 0.31 and 1.2%. Also, Taylor and Druckenmiller (2022) show that a one standard deviation increase in upstream wetlands increases National Flood Insurance Program (NFIP) claims by about 50% of the unconditional mean change in insurance claims.

Collectively, these results provide causal evidence for the power of wetlands in decreasing the local cost of debt. As discussed in Section I.A, when a wetland is converted into a developed area, the area loses the protection that wetlands provide against flooding and increases capital exposure to flood-prone areas. The DID approach disentangles these two effects and identifies the impact of wetlands loss upstream, controlling for local changes in wetlands.

The estimates show the increase in borrowing costs for new annual municipal debt issued by a median county can be as high as $5,309 for each hectare of upstream wetland lost or $4 million for a one standard deviation.[16] In other words, one standard deviation loss in upstream wetlands is related to an increase of 11% in interest expense on bonds outstanding. In addition, the loss to bondholders' wealth is estimated to $6.3 billion for counties that experienced a loss in upstream wetlands.[17]

C. Potential Channels: Extreme Weather Risk and Local Cash Flow

C.1. Natural Capital Loss and Local Extreme Weather Risk

In this section, I investigate potential channels that link natural capital loss to bond yields. First, Taylor and Druckenmiller (2022) provide causal evidence of the link between wetland loss and local extreme weather risk. Specifically, they find that one hectare loss in upstream wetlands is related to an increase in flood insurance claims between $1,840 and $8,000. Hence, since municipal bond prices reflect the present value of future cash flows backing the bonds and the probability of negative shocks, the loss of nature should affect municipal bond yields through the extreme weather risk channel.

I provide robustness to the results in Taylor and Druckenmiller (2022) by analyzing another proxy of local extreme weather risk: weather damages. I utilize the same approaches described in Section III.A and report the results in Table IV. I find that a one-hectare loss in upstream wetlands is related to an increase in weather damages of $13,621.[18] This evidence shows that a loss in wetlands affects local extreme weather risk.

[16] I utilize the modified duration approach to compute the impact of nature loss on local borrowing costs. $5,309 = $87.2 M (median annual issuance) × 9.81 years (median bond duration) × (0.063 b.p. / (1 + (3% / 2))). $4 M = $87.2 M × 9.81 years × ((0.063 b.p. × 748) / (1 + (3% / 2))).

[17] $6.3 B = ($891 M (median bond outstanding for affected counties) × 9.93 years × ((0.063 b.p. × 122 (average upstream wetland loss)) / (1 + (3.04%/2)))) × 947 counties.

[18] The results are qualitatively similar when utilizing as the dependent variable the difference between the average weather damages between 2005 and 2006 and the average weather damages between 2015 and 2016.

C.2. Natural Capital Loss and Local Tax Reliance

Another complementary channel regards local tax revenue. In particular, the expected local cash flows available to repay municipal bonds decrease after an extreme weather event (e.g, Jerch, Kahn, and Lin (2023)). Hence, natural capital is directly linked to local revenue via its ability to mitigate extreme weather events. It follows that counties most reliant on local revenue should see higher increases in yields. Using the Census of Governments data, I measure local revenue reliance as the ratio of local revenue to total revenue.[19] The local revenue ratio is used to sort counties into quintiles. Then, I run separate regressions for each quintile utilizing the same upstream-downstream difference-in-difference approach as in eq. (4).

The results in Figure 3 are in line with the findings in Goldsmith-Pinkham et al. (2021) and show that counties most dependent on local revenue see the highest yield increases. Specifically, counties in the highest quintile of local revenue reliance experience a statistically significant increase in yields of 0.093 b.p. (t-stat $= -3.43$) for each hectare loss. On the other hand, the counties in the lowest quintile of local revenue reliance see a statistically insignificant decrease in yields of 0.01 b.p. (t-stat $= 0.71$) for each hectare of upstream wetlands lost.[20] Overall, these findings suggest that natural capital loss affects local cash flows through increased climate change risk exposure.

D. Cross-sectional Analysis

D.1. Precipitation Intensity

I test if wetlands have differential effects on municipal bond yields during different levels of precipitation. Specifically, I utilize a panel fixed effect model since both bond yields and precipitation can be observed at high temporal frequency.

$$Y_{cst} = \beta_1 W_{cst} + \beta_2 W_{cst}^{UP} + \beta_3 W_{cst}^{ALL} + \lambda' X_{cst} + \delta_{st} + \delta_c + \epsilon_{cs}, \tag{4}$$

[19] The sources of general revenue of the local governments include intergovernmental (IG) revenue from the federal and state governments and local revenue.

[20] The results are qualitatively similar when utilizing the Herfindahl-Hirschman Index (HHI) index instead of the local revenue ratio.

where δ_{st} and δ_c represent state-year and county fixed effects. Y_{cst} represents the county-level volume-weighted monthly average yield. The changes in wetlands for this analysis are measured in 2006, 2011, and 2016.[21]

To clarify the impact of precipitation, I utilize each county's precipitation distribution to define five precipitation bins. Specifically, I create five indicator variables that equal one for each month with precipitation below average, between 0 and 1 standard deviation (σ) above the mean, between 1 and 2-σ above the mean, and above 3-σ, respectively.[22] Then, I add a linear interaction between each indicator variable above, the upstream wetland change, and the change in all wetlands. I exclude the indicator variable for precipitation below average and use this precipitation level as a reference. Figure 3 shows that almost all the increase in bond yields happens during months with precipitation above 3-σ. In particular, one standard deviation loss in local wetlands is related to an increase of 0.37% in bond yields.[23] This finding suggests that investors price natural capital loss only when the county experiences extreme precipitation.

D.2. Ultimate Land Use

It is plausible that the effect of wetlands loss is heterogeneous across ultimate land use. For instance, the impact on local flood risk is different if a wetland is replaced by an apartment complex instead of cropland since cropland can absorb some of the water from excess precipitation. To test this hypothesis, I utilize the same model as in eq. (4) and run separate regressions for each ultimate land use category.[24] Figure 3 shows that the impact of wetland loss on bond yields is stronger for developed areas but still economically and statistically significant for cropland and pasture. Specifically, for wetland loss due to development, one standard deviation loss in upstream

[21] The panel fixed effect model is not utilized in the main analysis since utilizing higher frequency data on wetlands introduces additional concerns related to measurement error and misclassification of wetlands (Taylor and Druckenmiller (2022)).

[22] The distribution of monthly local precipitation is approximately normal.

[23] The results are qualitatively similar when estimating eq. (4) for each precipitation intensity bin separately and when identifying extreme precipitation months using the precipitation in upstream areas instead of local precipitation.

[24] Over 50% of wetlands gains and losses entail a transition to and from open water. Excluding open water, development accounts for 35% of wetlands loss and 0% of wetland gain. Cropland and pasture constitute 35% of wetland loss and 58% of wetland gain. The remaining 30% of wetland loss and 42% of wetland gain is attributable to other natural areas (forest, grassland, shrubland, open areas, and barren land).

wetlands is related to an increase in bond yields of 0.59% over eleven years.

D.3. Farming Communities

Farming is one of the sectors most exposed to extreme weather and water stress. For this reason, nature conservation might be most important for farming communities. Thus, it is likely that counties that are more economically dependent on farming would be affected most by natural capital loss. To test this conjecture, I exploit the county-level heterogeneity in economic dependence and define a farming indicator that equals one for counties classified as dependent on farming by the Economic Research Service of the U.S. Department of Agriculture.

I estimate the effect of wetlands loss on municipal bond yields using the same approach as in the baseline estimates and limiting the sample to farming-dependent counties. The results in Figure 3 show that one standard deviation loss in wetlands results in an increase in bond yields of 0.55% (0.074 b.p. $\times$ 748 hectares) over eleven years. This evidence suggests that the effects of natural capital loss are more prominent in agricultural counties and can affect the whole country through food production disruptions.

E. When is Nature Loss Priced?

Investors should account for the value of natural capital when pricing municipal bonds since nature provides mitigation from extreme weather and adaptation to 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 would become salient to investors after a shock related to local climate change risk. The results described in Section III.D.1 provide evidence for this conjecture. However, the wetlands data does not provide a high-frequency estimate of when the wetland area is lost or gained. Hence, I further test this hypothesis using a quasi-experiment setup and analyze the behavior of municipal bond markets around a natural capital loss event and an extreme weather event. In particular, I compare the volume-weighted average yields of counties that experienced a loss in natural capital to those that did not.

As highlighted in Figure 1, the ideal experiment would entail comparing counties with similar characteristics and natural capital stock. For example, at time t, county B loses part of its natural capital and, at time $t+1$, an extreme weather event hits both county A and county B. This empirical design aims to compare bonds that trade in the same year, from the same state, and have similar observable characteristics, except for having experienced a natural capital loss event or not. Hence, the sample includes counties that experienced extreme weather events and contain protected areas.[25]

E.1. Natural Capital Loss Shocks

I identify counties that experience a loss in natural capital using the Protected Area Downgrading, Downsizing, and Degazettement or PADDD dataset (Conservation International and World Wildlife Fund (2021)).[26] Downgrading is a decrease in legal restrictions on the number, magnitude, or extent of human activities within a protected area (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)).

As noted in the ecology and conservation literature, these events threaten critical areas with the ability to mitigate extreme weather and climate change, preserve biodiversity, and protect the water cycle. For instance, when commercial activity is allowed in a protected area or a new infrastructure is built, some vegetation is removed. Thus, the area loses some of its flood mitigation abilities, such as holding and absorbing excess water and reducing the speed of floodwater during extreme precipitation events.

The reasons for the enactment of PADDD vary from industrial-scale resource extraction and development to land claims and local land pressures. A small fraction of the PADDD is meant

[25]A county that experienced natural capital loss is not included in the control group for other cohorts to avoid biased estimates (Borusyak and Jaravel (2017) and De Chaisemartin and d'Haultfoeuille (2020)).

[26]In this paper, 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)).

for conservation planning (Mascia and Pailler (2011)). The PADDD enactment is performed by the federal government through legislation and federal agencies' regulations (e.g., U.S. Fish and Wildlife Service).

E.2. Exogeneity of Natural Capital Loss Shocks

Some county characteristics are inherently different between counties that experience a PADDD and those that do not. First, as we can see from Table I, among other characteristics, counties that lose natural capital have more protected areas on average, higher real estate value, and higher population. However, these relations should not be interpreted as causal due to the presence of confounding factors and omitted variables that could be driving the correlation. For instance, counties with more protected areas will be more exposed to PADDD. In addition, proximity to nature is correlated to higher real estate prices (e.g., Chamblee et al. (2011)). Also, areas with wetter climates are more likely to face flood events and have more wetlands. Hence, to ensure the validity of the quasi-experiment, I use a set of control variables that account for observable and unobservable county characteristics.

A few elements suggest that PADDD events might be unrelated to local economic activity. Specifically, PADDD needs to be approved at the federal level, and often, the regulations that trigger a PADDD are not specific to a single protected area.[27] On the other hand, I acknowledge that these events might not be random. For instance, even though the federal government approves the PADDD, policymakers may consider local county economic characteristics and trends during the decision-making process. In addition, local governments might bargain with the federal government before the regulations are passed.

The cause listed for the majority (76.5%) of events during the sample period from 2005 to 2020 is subsistence, defined as non-commercial or small-scale commercial, access expansion, artisanal, or non-industrial (non-mechanized) extraction or production activities. The need for these activities would likely not be influenced by local economic conditions. In particular, these subsistence PADDD

[27] For instance, the U.S. Fish and Wildlife Service expanded hunting and fishing and allowed for construction that facilitates access to many National Wildlife refuges affecting counties in 16 states.

events do not seem to be related to local unobservable economic trends and characteristics, but entail the clearing of vegetation on at least 186 hectares.

For instance, in 2018, a federal regulation by the U.S. Fish and Wildlife Service opened or expanded hunting and sport fishing and allowed constructions that facilitate access in National Wildlife Refuges such as the Charles M. Russell National Wildlife Refuge and Felsenthal National Wildlife Refuge for a total of 251,000 acres. Another subsistence PADDD allowed small commercial activities in Sequoia and Kings Canyon Park. These activities possibly fragmented these natural areas affecting their adaptation and disaster mitigation abilities (Kroner, Krithivasan, and Mascia (2016)).

Other PADDD events during the sample period are related to resource extraction and infrastructure. For example, in 2005, the federal government allowed seismic explorations for oil and gas within the Gulf Islands National Seashore. In 2011, the Ski Area Recreational Opportunity Enhancement Act allowed for expanding ski-related infrastructure in a few national parks (e.g., Shawnee National Forest, Ouachita National Forest, and Kisatchie National Forest).[28] During these events, trees and other vegetation were removed together with soil disturbance, which most likely weakened the disaster mitigation ability of these natural areas.

Regarding political affiliation, I find no evidence that Republican counties are more likely to experience a PADDD event, both unconditionally and conditional on the ratio of protected area to total county land area. Lastly, it is unlikely that omitted drivers of PADDD could affect the sensitivity of local government finances to extreme weather risk.

E.3. Extreme Weather Events

I select extreme weather events using extreme local precipitation. The months selected as extreme weather events are months in which a county experienced average precipitation greater

[28] Two downsizing events attracted considerable media attention: the downsizing of Bears Ears National Monument and Grand Staircase-Escalante National Monument in 2017. Even though these events seem to be strictly related to resource exploitation, it is unlikely that ex-ante local economic conditions affected the decision to allow fossil fuel and mineral exploration in these parks. For robustness, I replicate the analysis by excluding these two PADDD events. The results are qualitatively similar to the main results.

than the 95^{th} percentile of the distribution of past precipitation.[29] The sample from 2005 to 2020 includes 175 event-month cohorts. During these months, the counties selected faced exceptional levels of precipitation which likely disrupted regular business and destroyed property and crops.

E.4. Identification Strategy

The difference-in-differences model used for the estimation of the natural capital effect around an extreme precipitation event is as follows:

$$Y_{cst} = \sum_{\tau=-5,\tau\neq-2}^{5} \lambda_\tau 1(Month=\tau) + \sum_{\tau=-5,\tau\neq-2}^{5} 1(Month=\tau)\,(\gamma_\tau Treated_{cst}) + \theta'\,X_{cst} + \delta_{st} + \delta_{cs} + \epsilon_{cst}. \quad (5)$$

This model is estimated using the bonds trading in month t issued in county c (located in state s). Y_{cst} represents the county-level volume-weighted monthly average yield. $Treated$ is an indicator that equals one for a county that has experienced natural capital loss and an extreme weather event. X represent a vector of control variables. Lastly, δ_{st} and δ_{cs} represent state-year-month and county fixed effects, respectively. The sample includes only counties that experience extreme weather events.

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 and the control group. Specifically, I consider a county as treated if a PADDD was enacted between year $y-5$ and $y-1$ from the weather event. I choose this time window since it is plausible that the loss of natural capital is not immediate after the PADDD event is enacted.[30] In addition, the initial stages of an infrastructure project will entail vegetation clearing before the infrastructure is built. Hence, the results reported in this study likely represent increased extreme weather risk related to natural capital loss and not increased capital at risk.

The vector of control variables, X, includes the same county and bond characteristics described in the main analysis. In addition, I add $Weather\,Exp._{1-5}$ and $Weather\,Exp._{6-10}$, which represent

[29] In unreported results, I utilize the 90^{th} and 98^{th} percentiles of the distribution of past precipitations to define the extreme weather months and find qualitatively similar results.

[30] The results are qualitatively similar when using PADDD events enacted between $y-7$ to $y-2$ and $y-10$ to $y-2$ from the weather event. These results are reported in Table IAIII of the Internet Appendix.

the precipitation exposure from year $y-1$ to $y-5$ and year $y-6$ to $y-10$, respectively.[31] These measures reduce the concern that the results reported are caused by differences in extreme weather exposure and pre-existing disaster mitigation programs. Only pre-event time-varying characteristics are included to avoid biased estimates.[32]

The use of state-year-month 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 month. The county fixed effects account for any time-invariant differences in county characteristics. Also, the use of county fixed effects allows me to compare counties with similar protected areas since these natural areas rarely change in size. Collectively, the shock to natural capital loss and the fixed effects diminish the concerns that the county's natural capital stock is related to unobserved economic characteristics that could bias the results.

E.5. Natural Capital Loss Shocks and Municipal Bond Yields

Table V and Figure 4 report the results of the difference-in-differences analysis using the county-level volume-weighted average bond yields as the dependent variable. Columns (1) and (2) include all bonds in the sample and, in columns (3) and (4), I split the sample into revenue and general obligation bonds, respectively. I utilize $t-2$ as a reference since some extreme weather events could be forecasted, and markets might reflect this forecast accordingly.

The coefficients in columns (1) to (4) show that the difference between treated and control counties, or the "nature premium," turns from statistically indifferent from zero to positive and significant after the extreme weather event for all months except for one (month 4). The effect is stronger for revenue bonds (column (3)), possibly because these bonds are backed by the revenue of

[31] These measures are calculated using the maximum standardized precipitation that the county experiences from year $y-1$ to $y-5$ and from year $y-6$ to $y-10$. This choice is due to the rare nature of extreme weather events. The results are qualitatively similar when using ex-ante weather damages instead of precipitation intensity.

[32] Including post-event control variables that might themselves be affected by extreme precipitation (i.e., "bad controls") would result in biased estimates and the coefficient of interest would not have a causal interpretation (Angrist and Pischke (2009) and Angrist and Pischke (2014)). In the specifications without county fixed effects, I include the following time-invariant county characteristics: quintile indicators for the ratio of natural capital area to total county land area, proximity to the coast, and elevation.

the specific project and not by the overall municipal tax revenue. The results are qualitatively similar when increasing the event window to twelve months before and after the extreme precipitation event (Figure 4 Panel B).

These estimates are economically meaningful. The yields change from statistically indifferent from zero to between 10 and 19 basis points, which corresponds to an average pre-post spread of 5.6% of the bond yield sample mean (3.04%). To better understand the impact of nature loss, I estimate the effect on bondholders' wealth. Specifically, the outstanding municipal debt for all counties affected by PADDD during the year of the extreme weather event equals about $180 billion. Using the modified duration approach on a semiannual basis, bondholders' wealth decreases by $2.45 billion.[33]

On the other hand, as shown in Table IAIV of the Internet Appendix, I find no evidence of a market response after a natural capital loss event. Specifically, after a PADDD event, the difference in yields between the treated and control groups is statistically indifferent from zero.[34] This evidence suggests that investors price nature loss risk "implicitly" after an area is hit by extreme precipitation and the increase in extreme weather risk due to nature loss becomes more salient.

As opposed to the results in Table V, Auh et al. (2021) find that natural disasters do not affect general obligation bonds except for counties with distressed financial conditions. This difference is likely to be due to the following two reasons. First, the two studies differ in the definition of treated and control groups due to their distinct goals. Specifically, I identify the treatment using natural capital loss and extreme weather events. 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. Second, I utilize precipitation, a purely exogenous event, to identify shocks to the county's climate change risk compared to the normalized damage measure used in Auh et al. (2021).

[33] $\$2.45$ B = $\$180$ B $\times$ 8.13 years (average duration) $\times$ (0.0017 / (1 + (3%/2)).

[34] I also find no difference in the issue volume between the treated and control group after a PADDD event.

E.6. Natural Capital and Offering Yields

After discussing the effect on municipal bond yields in the secondary market, I analyze the impact of natural loss on the primary market by evaluating the implications for offering yields. I utilize a similar approach to Gao, Lee, and Murphy (2020) and estimate the following DID model.

$$Off.Yields_{cst} = \gamma_1 Treated_{cst} \times Post_{cst} + \gamma_2 Treated_{cst} + \gamma_3 Post_{cst} + \theta' X_{cst} + \delta_{st} + \delta_{cs} + \epsilon_{cst}, \quad (6)$$

The dependent variable represents a volume-weighted average of the offering yields at the county level. $Treated$ is an indicator that equals one for a county that has experienced natural capital loss and an extreme weather event. $Post$ is an indicator equal to one for the period after the extreme weather event. The estimation window starts three years before the extreme weather event and ends three years after it.

The results reported in Table VII show an increase in offering yields of 5.58 basis points. For an average county, this effect translates to an increase in borrowing costs of \$0.7 million or 2% of a median county's annual interest expense on bonds outstanding.[35] The economic magnitude of the results varies and is as much as three times larger for counties exposed to extremely large levels of precipitation. The insights from this analysis also show that the nature premium is not short-lived. However, the estimates from the offering yields in the primary market can be affected by the local government's attempts at market timing. In particular, the local government might wait or anticipate the bond issuance during periods of low disaster risk.

[35] I utilize the modified duration approach to calculate the increase in borrowing costs. \$0.7 M = \$87.2 M (median annual issuance) × 10.61 years (median bond duration) × (0.000558/(1 + (3%/2)).

IV. Additional Tests and Robustness

A. Wetlands Robustness Tests

A.1. Only Counties Experience Flooding

Since flooding events are rare, it is possible that large wetland losses are not related to changes in yields because no flood event occurred during the sample period. In Table IAV of the Internet Appendix, I limit the sample to counties that experience flooding and find that the effect is stronger in magnitude.

A.2. Leave-one-out Estimation and Additional Tests

One state might be driving the results. I exclude this issue by estimating the model 49 times by excluding one state for each estimation. Figure IA1 shows that the effect is almost identical for each estimation showing that no one state is driving the results. In unreported results, I find that the coefficients are largely unchanged when including the number of extreme weather events over the sample period and limiting the sample to counties with at least 10 hectares of wetlands.

B. PADDD Robustness Tests

B.1. Spillover Effects

The effects of natural capital loss might not be limited to the county that possesses the natural capital. Due to spatial links, even counties not directly hit by natural capital loss might experience negative consequences during extreme weather events. To study this phenomenon, I specify five treatment areas within 25, 50, 100, 200, and 300 miles from the county that experiences the PADDD event.[36] For each of these treatment areas, I run separate estimations of the natural capital loss

[36] 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).

effect and exclude the counties in the range previously analyzed. For example, the treated sample for the 25-mile analysis excludes counties directly affected by PADDD.

I use the same empirical approach as in Section III.E.4. The only difference is the use of neighboring counties to define the treated and control groups. The results in Figure 5 show that the flood risk mitigation effect of natural capital extends to neighboring counties. For example, the treated sample in the 25-mile radius from PADDD experiences an increase in yields between 15 and 17 basis points compared to the control group.

Also, the estimates show that the effect is still statistically significant at the 10% level for counties within 50 miles from the PADDD event but at least 25 miles away. The impact of natural capital loss seems to decrease when the sample includes counties within 100 miles of the county affected by PADDD.[37] Lastly, the results are robust when using matched treated and control samples as described in the Internet Appendix.

B.2. Exogeneity Tests and the Validity of the Experiment

To address the concerns related to pre-existing economic trends, I estimate the direct economic effect of natural capital loss with an event study approach that uses PADDD events as the exogenous shock and to define the treatment and control groups. The specifications are identical to the ones described in Section III.E.4, except that the variables are measured at the annual level and I use year indicators.[38] Figure IA2 shows that there are no discernible differences in trends for population, personal income, unemployment rate, or local revenue between counties that experience natural capital loss and those that do not in the period before or after the natural capital loss.[39] Hence, I find supporting evidence for the parallel trend assumption.

[37]In unreported results, I compare the yields of counties that lose natural capital to those that did not before and after a neighboring county experiences an extreme weather event, i.e., "near miss" counties. I find no significant difference in yields between the treated and control group among "near miss" counties.

[38]The results are qualitatively similar when including post-event characteristics as control variables for these exogeneity tests.

[39]The results are qualitatively similar when using level measures instead of changes. I also find no difference in bond issuance volume before and after the PADDD or before and after the extreme weather event. Lastly, I find no difference in population, personal income, unemployment, or local revenue between the treated and control group in the period before the extreme weather event.

In addition, I use extreme weather events as purely exogenous shocks to local economic activity and climate risk awareness to identify the adaptation value of nature. At a minimum, the results reported are the manifestation of a treatment effect on the treated.

The subsistence events might not be strong enough to affect the disaster-mitigating ability of nature, even though the environmental literature states otherwise. Hence, I split the sample into two groups: PADDD caused by subsistence and all PADDD causes except subsistence. The results in Table VIII Panel A (columns (4)-(5)) show that both samples report a "nature premium," suggesting that any nature disturbance affects nature's disaster mitigation ability. Table VIII Panel B also shows that the results are robust when extending the estimation window to seven years. The coefficient estimates are economically and statistically similar when utilizing less stringent fixed effects specifications as reported in Table IAVI in the Internet Appendix.

Although unlikely, the results could be confounded by the intensity of extreme weather events in areas affected by natural capital loss. If 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 mitigate the impact of this possible source of bias, I analyze the difference in weather intensity between the treated and control groups using the monthly raw and the standardized precipitation for the extreme weather months used to define the shocks. The differences between the two measures for the two samples are statistically indifferent from zero (0.009, t stat = 0.009; 0.017, t stat = 0.093).

B.3. Additional Tests

In the cross-section, I find that the following bonds see the highest increase in yields: bonds issued for infrastructure projects, bonds issued by farming communities, bonds issued after 2012, and bonds with a maturity greater than ten years (Table IAVII and Table IAVIII in the Internet Appendix). In addition, I report no significant difference between bonds issued by Republican counties or counties most worried about climate change. I find no difference between counties that experience a proposed PADDD and those that do not. Lastly, I confirm that the estimates are qualitatively similar when utilizing municipal bond credit spreads following Goldsmith-Pinkham et al. (2021) and are not driven by one specific state or the PADDDs in 2016. Additional descriptions of these tests and more robustness tests are provided in the Internet Appendix.

V. Summary and Conclusions

Nature provides one of the best technologies to fight global warming and mitigate the impact of natural disasters. Thus, local economic activity can be seriously affected by nature loss. This is the first study to estimate the impact of nature loss on municipal bonds and local borrowing costs. Specifically, using satellite data on wetlands, I show that wetland loss increases municipal bond yields and can increase the counties' cost of debt by increasing local flood risk and local cash flow risk. Also, I find that investors price nature loss risk after the county experiences an extreme precipitation event.

The nature loss effect is more prominent when wetlands are converted into developed areas as well as in farming counties, revenue bonds, and bonds funding infrastructure. The loss of natural capital has long-term implications for the local borrowing costs reflected in yields and credit ratings. In addition, the effects of natural capital loss are not limited to the counties that possess this capital but also to their neighboring counties.

The relation between nature conservation, local cost of debt, and climate change risk should be of interest to policymakers. Nature conservation might also affect other assets (e.g., real estate and commodities), firms, and households. Studying these assets and stakeholders would further highlight the importance of nature. Also, the role of natural capital might not be limited to disaster mitigation and might directly affect the value of local firms. Another interesting avenue for future research would be to examine the drivers and constraints that determine municipalities' choice to invest in disaster risk mitigation.

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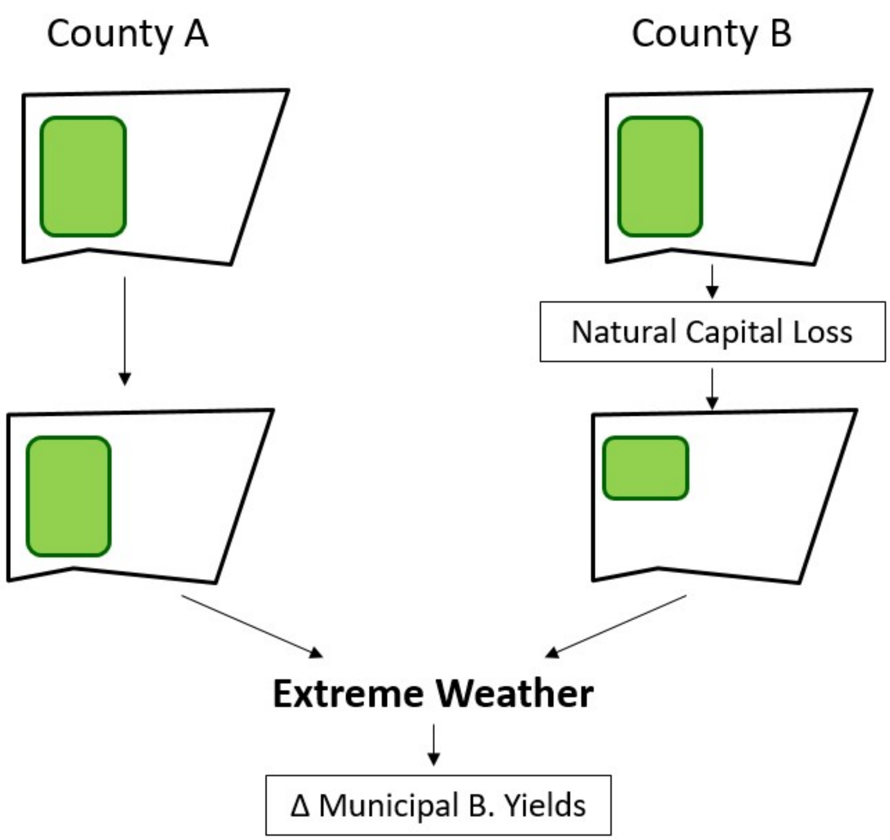
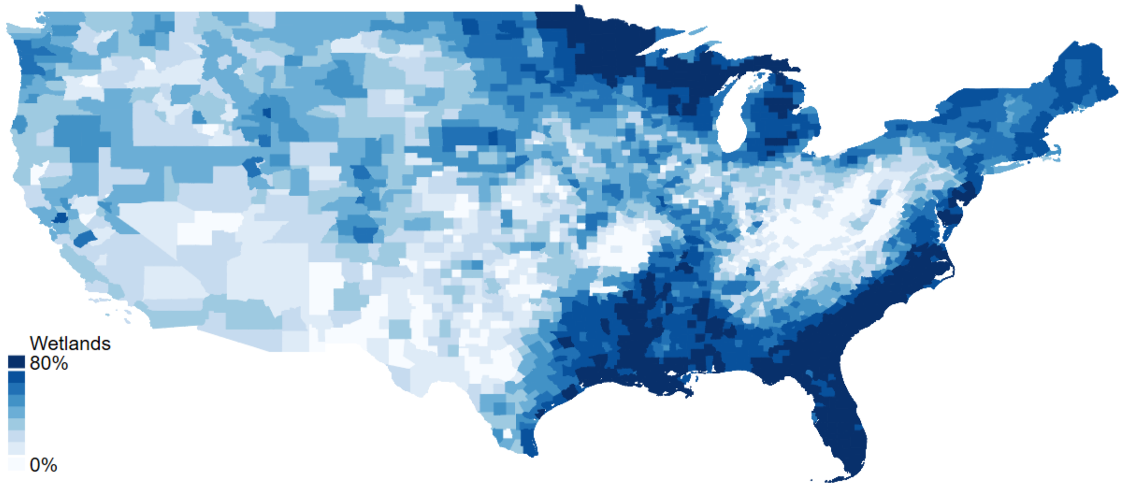


Figure 1: Ideal Experiment - Natural Capital Loss Pricing
This figure describes the quasi-experiment utilized in Section III.E.

Panel A: Wetlands across the U.S.



Panel B: Wetland Area Gains and Losses

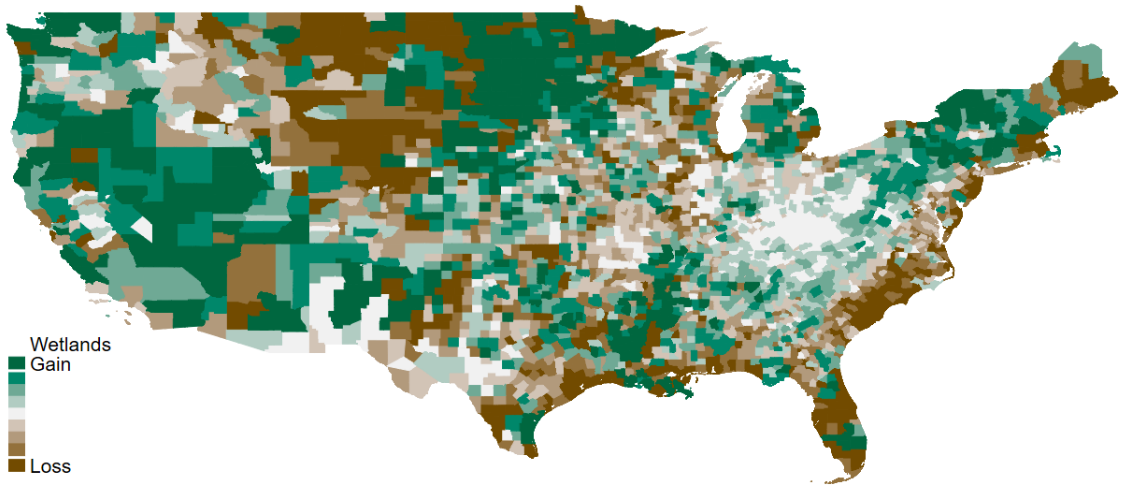


Figure 2: Wetlands in the U.S.
The figure in Panel A reports the percentage of area covered by wetlands using a blue scale. In Panel B, the green and brown coloring represent the gain and loss in wetlands from 2006 to 2016.

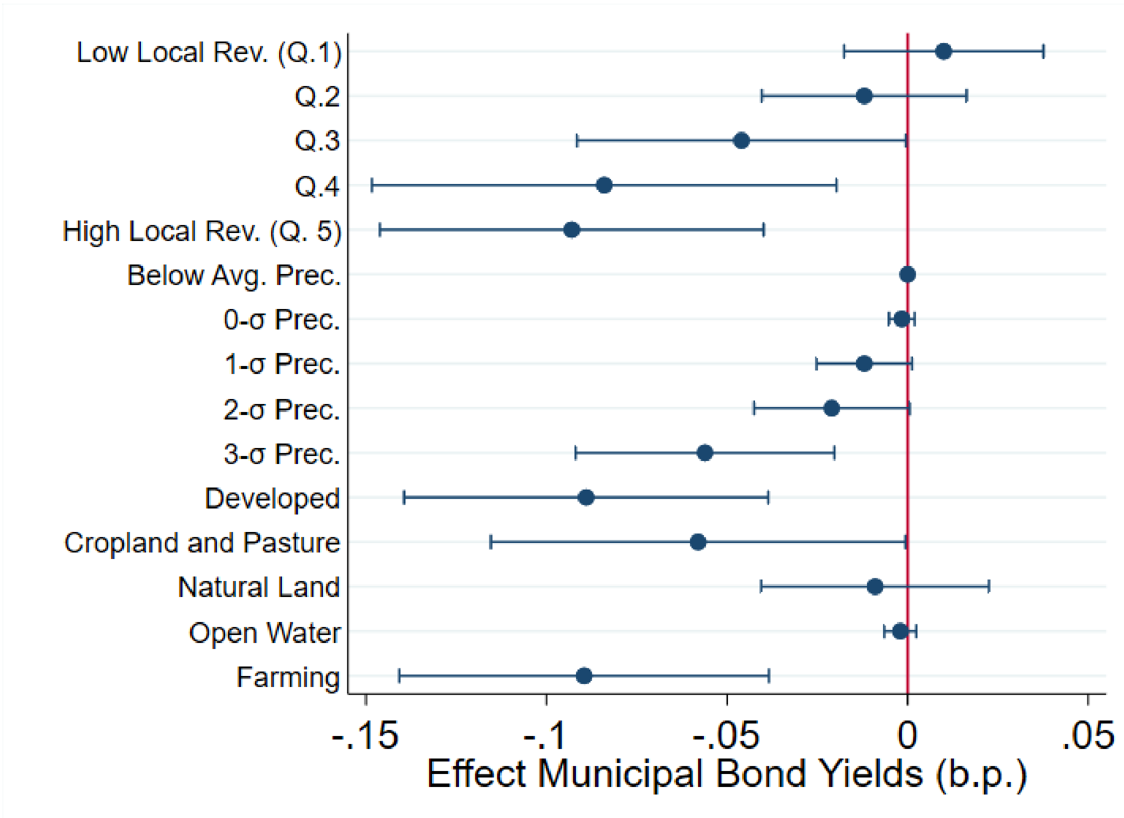
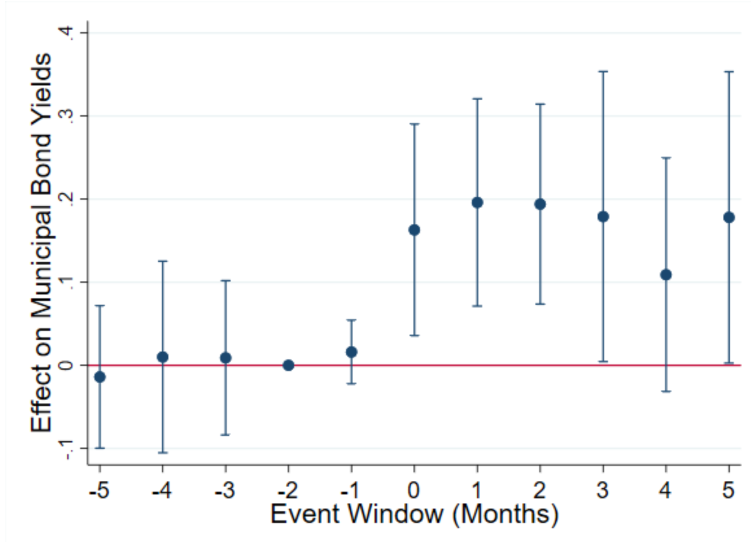


Figure 3: Cross-sectional Effect of Upstream Wetlands Change
This figure represents the cross-sectional estimates of the effect from one-hectare loss in upstream wetlands on municipal bond yields (eq. (4)). The estimates include the effect across local revenue reliance, precipitation (prec.) intensity, ultimate land use (developed, cropland and pasture, natural land, and open water), and economic dependence (farming). For local revenue reliance, the ultimate land use, and farming, the blue dot represents the coefficient of the term W_{cs}^{UP}. For the precipitation intensity, the blue dot represents the interaction between W_{cs}^{UP} and the indicator variable for each precipitation intensity bin (farming indicator). The horizontal lines represent 95% confidence bands. The control variables include county characteristics and municipal bond characteristics averaged at the county level. The specifications include state fixed effects. The standard errors are clustered by county.

Panel A: Natural Capital Loss and Bond Yields - $t-5$ to $t+5$ Months



Panel B: Natural Capital Loss and Bond Yields - $t-12$ to $t+12$ Months

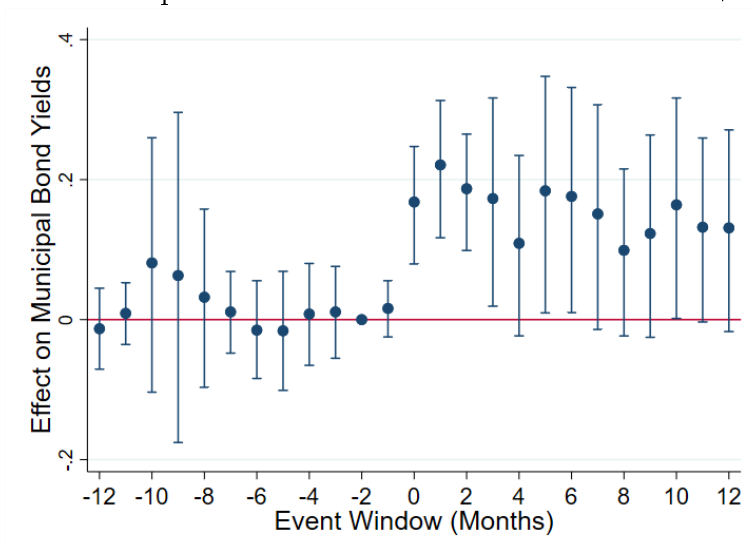


Figure 4: Natural Capital Loss and Bond Yields
The figure in Panel A represents the coefficients from the difference-in-differences regression of monthly county-level volume-weighted average municipal bond yields before and after an extreme weather event (eq. 5). Panel A reports the results as in Table V column (2). Instead, Panel B reports the results with an extended event window from $t-12$ to $t+12$ months from the extreme weather event. The vertical lines represent 95% confidence bands. The coefficients are estimated using month $t-2$ as a reference. The control variables include county characteristics, municipal bond characteristics averaged at the county level, and the intensity of the weather event. The specifications include state-year-month and county fixed effects. The standard errors are clustered two ways by county and year-month.

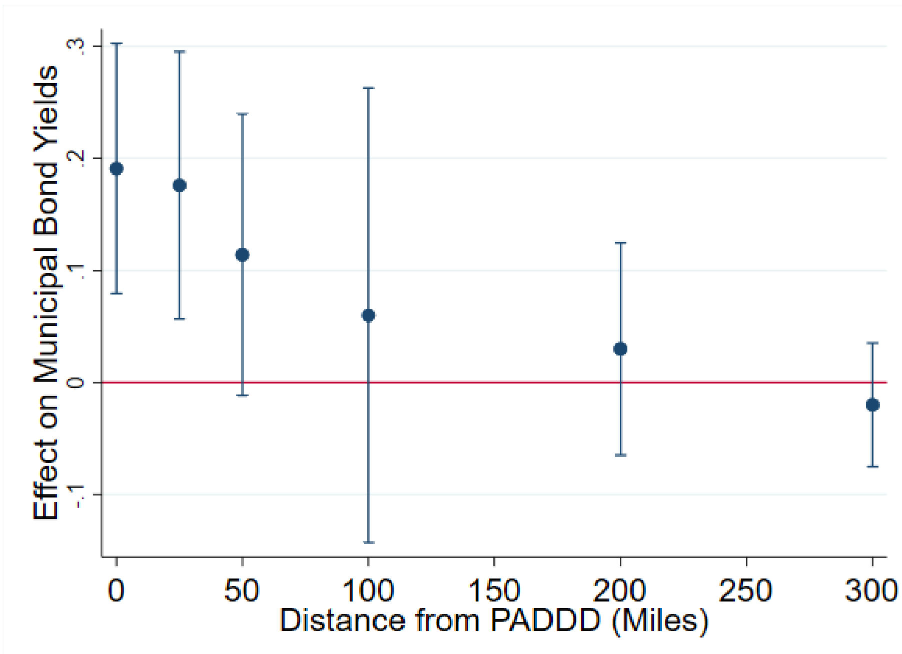


Figure 5: Spillover Effect of Natural Capital Loss
This figure represents the coefficients from the difference-in-differences regressions of monthly county-level volume-weighted average municipal bond yields before and after an extreme weather event. The coefficients reported are estimated using the approach as in Table VIII. Each point represents a separate estimation using the respective distance from the PADDD county to define the treated and control groups. The blue dot represents the coefficient of the term $Treated \times Post$. The vertical lines represent 95% confidence bands. The control variables include county characteristics, municipal bond characteristics averaged at the county level, and the intensity of the weather event. The specifications include state-year-month and county fixed effects. The standard errors are clustered two ways by county and year-month.

Table I: Summary Statistics

Panel A reports summary statistics for the wetland areas. Panel B reports summary statistics for the variables used in the paper for two groups of observations: counties that experienced a PADDD event and those that did not.

Panel A: Wetland Characteristics

	Mean	St. Dev.	Obs.	Min.	Max
Wetland Area, 2006 (ha)	14,611	33,486	3,209	0	726,492
Wetland Area, 2016 (ha)	14,684	33,706	3,209	0	727,078
Wetland Change, 2006 to 2016 (ha)	13	655	3,209	−6,362	14,497
Wetland Gain (ha)	106	523	3,209	0	14,497
Wetland Loss (ha)	−93	368	3,209	−6,362	0

Panel B: County Characteristics

	PADDD			No PADDD				
	Mean	St. Dev.	Obs.	Mean	St. Dev.	Obs.	Diff.	*t*-stat
Avg. Yield-to-Maturity (%)	3.04	1.93	14,583	3.02	1.10	75,728	0.02	0.61
Avg. Offering Yield	2.97	1.61	14,583	2.95	1.69	75,728	0.02	1.35
Avg. Rating	3.43	1.49	14,583	3.44	1.52	75,728	−0.01	−0.74
Avg. Maturity (years)	14.71	7.73	14,583	15.43	7.07	75,728	−0.10	−1.49
Weather Damages ($M)	2.59	37	8,650	3.01	64.05	126,321	−0.41	−0.95
Weather Exp.	0.11	1.01	8,650	0.36	0.85	126,321	−0.24***	−21.84
Population	60,521	109,514	8,650	44,985	81,882	126,321	15,536***	12.95
Population Trend (%)	1.13	2.47	8,304	1.09	2.03	126,321	0.04	1.44
Density	43	65	8,650	70	128	126,321	−26.59***	−33.68
Personal Income ($)	19,561	14,721	8,650	19,138	12,875	126,321	423.29***	2.61
Unemployment	6.12	2.81	8,650	6.98	3.01	126,321	−0.86***	−27.41
Urban-Rural Classification	5.25	1.00	8,650	5.30	1.04	126,321	−0.05***	−4.22
Protected Area (%)	18.32	15.62	8,650	3.28	5.85	126,321	15.04***	89.12
Republican (%)	55.82	15.25	8,650	55.58	15.01	126,321	0.24	1.42
Worried - Climate Change (%)	46.96	5.23	8,650	46.83	5.14	126,321	0.13**	2.24
FEMA Transfer ($M)	2.65	48	8,650	2.88	52	126,321	−0.23	−0.43
Debt/Tax Revenue	3.68	8.28	8,650	3.72	9.24	126,321	−0.04	−0.43
House Price Index	221,474	166,856	2,767	145,764	113,227	51,791	53,629***	23.58

Table II: PADDD Summary Statistics

This table reports descriptive statistics for the PADDD events enacted in the U.S. (excluding Alaska and Hawaii) sorted by year, urban-rural classification, and cause. For Panel A, the sample period is 1969-2020. For Panels B and C, the sample period is 2005-2020.

Panel A: PADDD by Year

Year	Counties Affected	Percent	Area Affected (km^2)	Area Affected (mi^2)
1976	1	0.21	1	1
1978	1	0.21	40	15
1980	4	0.82	3,205	1,237
1986	102	20.99	8,445	3,261
1987	3	0.62	370	143
1988	5	1.03	1,140	440
2000	4	0.82	5,229	2,019
2005	5	1.03	29	11
2007	4	0.82	1,139	440
2011	40	8.23	5,684	2,194
2012	25	5.14	4,455	1,720
2016	235	48.35	31,859	12,301
2017	4	0.82	3,388	1,308
2018	45	9.26	6,822	2,634
2019	8	1.65	8,073	3,117
Total	486	100	79,879	30,842

Panel B: PADDD by Urban-Rural Classification

Urban-Rural Classification	Freq.	Percent	Area Affected (km^2)	Area Affected (mi^2)	% of Total Area Affected
Large Central Metro	14	3.83	6,294	2,430	11.52
Fringe Metro	30	8.20	6,201	2,394	11.35
Medium Metro	64	17.49	9,218	3,559	16.87
Small Metro	46	12.57	8,331	3,217	15.25
Micropolitan	78	21.31	9,793	3,781	17.93
Non-core	134	36.61	14,790	5,710	27.07
Total	366	100	54,627	21,092	100

Panel C: PADDD by Cause

Cause of PADDD	Freq.	Percent	Area Affected (km^2)	Area Affected (mi^2)	% of Total Area Affected
Subsistence	280	76.50	31,859	12,301	68.43
Infrastructure	50	13.66	5,382	2,078	11.56
Land Claims	20	5.46	3,679	1,421	7.90
Oil and Gas	5	1.37	29	11	0.06
Mining	4	1.09	3,388	1,308	7.28
Other	7	1.91	2,216	856	4.76
Total	366	100	54,627	21,092	100

Table III: Wetland Changes and Municipal Bond Yields

This table reports the long differences (LD) and upstream-downstream difference-in-differences (DID) estimates with county-level volume-weighted municipal bond yields in the secondary market (columns (1)-(4)) and in the primary market, i.e., offering yields (columns (5)-(8)) as dependent variables. The changes in the local wetland area are defined at the county level. In columns (1), (2), (5), and (6), I model the response of bond yields and ratings to changes in wetlands area as linear. In columns (3), (4), (7), and (8), I allow for differential responses to gains and losses in wetland areas. Upstream wetland changes are defined as changes in wetlands in all areas upstream of the county under consideration. The control variables include changes in county characteristics, municipal bond characteristics averaged at the county level, weather exposure, and total changes within each county's watershed (both upstream and downstream). The standard errors are clustered by county. 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.

Dependent Variables	Yields (b.p.)				Offering Yields (b.p.)			
	LD	DID	LD	DID	LD	DID	LD	DID
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local Wetland Change (ha)	−0.039*	−0.031*			−0.038*	−0.033*		
	(−1.89)	(−1.73)			(−1.84)	(−1.71)		
Local Wetland Gain (ha)			−0.008	−0.007			−0.008	−0.008
			(−0.53)	(−0.44)			(−0.46)	(−0.43)
Local Wetland Loss (ha)			−0.044*	−0.041*			−0.042*	−0.039*
			(−1.92)	(−1.83)			(−1.89)	(−1.79)
Upstream Wetland Change (ha)		−0.063***				−0.062**		
		(−2.58)				(−2.15)		
Upstream Wetland Gain (ha)				−0.010				−0.009
				(−0.78)				(0.75)
Upstream Wetland Loss (ha)				−0.067***				−0.065**
				(−2.61)				(−2.34)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,827	1,827	1,827	1,827	1,827	1,827	1,827	1,827

Table IV: Wetland Changes and Weather Damages

This table reports the long differences (LD) and upstream-downstream difference-in-differences (DID) estimates with county-level weather damages as dependent variables. The changes in the local wetland area are defined at the county level. In columns (1) and (2), I model the response of weather damages to changes in wetlands areas as linear. In columns (3) and (4), I allow for differential responses to gains and losses in wetland areas. Upstream wetland changes are defined as changes in wetlands in all areas upstream of the county under consideration. The control variables include changes in county characteristics, municipal bond characteristics averaged at the county level, weather exposure, and total changes within each county's watershed (both upstream and downstream). The standard errors are clustered by county. 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.

	LD	DID	LD	DID
	(1)	(2)	(3)	(4)
Local Wetland Change (ha)	−7,118**	−3,876*		
	(−2.01)	(−1.73)		
Local Wetland Gain (ha)			−158	−126
			(−0.43)	(−0.41)
Local Wetland Loss (ha)			−7,358**	−4,053*
			(−2.08)	(−1.81)
Upstream Wetland Change (ha)		−13,621***		
		(−2.48)		
Upstream Wetland Gain (ha)				−149
				(−0.43)
Upstream Wetland Loss (ha)				−15,792***
				(−2.56)
Controls	Y	Y	Y	Y
State FE	Y	Y	Y	Y
Observations	1,827	1,827	1,827	1,827

Table V: Natural Capital Loss and Bond Yields - Extreme Weather Events

This table reports the difference-in-differences (DID) estimates with monthly county-level volume-weighted average municipal bond yields as dependent variables and extreme weather events as exogenous shocks. The sample in columns (1)-(2) includes all bonds. Columns (3) and (4) include only revenue and general obligation bonds, respectively. The Treated variable indicates municipal bonds of counties that experienced an extreme weather event and a PADDD event between $y-5$ and $y-1$ from the extreme weather event. The control variables include county characteristics, municipal bond characteristics averaged at the county level, and the intensity of the weather event. The specifications include state-year-month and county fixed effects. The standard errors are clustered two ways by county and year-month. 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)	(4)
Treated × 1(Month −5)	−0.014	−0.014	−0.015	−0.015
	(−0.34)	(−0.32)	(−0.41)	(−0.37)
Treated × 1(Month −4)	0.009	0.011	−0.010	0.014
	(0.19)	(0.20)	(−0.25)	(0.21)
Treated × 1(Month −3)	0.010	0.009	0.051	0.010
	(0.27)	(0.19)	(0.74)	(0.23)
Treated × 1(Month −2)				
Treated × 1(Month −1)	0.014	0.016	0.017	0.015
	(0.74)	(0.82)	(0.48)	(0.33)
Treated × 1(Month 0)	0.167***	0.163***	0.306***	0.144**
	(2.76)	(2.51)	(3.04)	(2.22)
Treated × 1(Month 1)	0.221***	0.195***	0.348***	0.188**
	(4.14)	(3.08)	(4.78)	(2.11)
Treated × 1(Month 2)	0.188***	0.194***	0.332**	0.185***
	(4.17)	(3.16)	(2.35)	(2.79)
Treated × 1(Month 3)	0.173**	0.179**	0.251**	0.131*
	(2.18)	(2.01)	(2.02)	(1.86)
Treated × 1(Month 4)	0.109	0.107	0.141	0.103
	(1.59)	(1.52)	(1.67)	(1.53)
Treated × 1(Month 5)	0.184**	0.178**	0.336***	0.143*
	(2.04)	(1.99)	(2.62)	(1.91)
Sample	All	All	Rev.	GO
Controls	Y	Y	Y	Y
State-Year-Month FE	Y	Y	Y	Y
County FE	N	Y	Y	Y
Observations	77,161	77,161	43,814	57,953
Adj. R^2	0.12	0.13	0.14	0.12

Table VI: Wetland Changes and Municipal Bond Yields - Revenue vs. General Obligation

This table reports the long differences (LD) and upstream-downstream difference-in-differences (DID) estimates with annual county-level volume-weighted municipal bond yields of Revenue bonds (columns (1)-(4)) and GO bonds (columns (5)-(8)). The changes in local wetland area are defined at the county level. In columns (1), (2), (5), and (6), I model the response of bond yields and ratings to changes in wetlands area as linear. In columns (3), (4), (7), and (8), I allow for differential responses to gains and losses in wetlands area. Upstream wetland changes are defined as changes in wetlands in all areas upstream of the county under consideration. The control variables include changes in county characteristics, municipal bond characteristics averaged at the county level, weather exposure, and total changes within each county's watershed (both upstream and downstream). The standard errors are clustered by county. 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.

	Revenue				General Obligation			
	LD	DID	LD	DID	LD	DID	LD	DID
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local Wetland Change (ha)	−0.044*	−0.034*			−0.037*	−0.030*		
	(−1.97)	(−1.78)			(−1.81)	(−1.69)		
Local Wetland Gain (ha)			−0.008	−0.008			−0.009	−0.008
			(−0.51)	(−0.53)			(−0.49)	(−0.46)
Local Wetland Loss (ha)			−0.051*	−0.043*			−0.037*	−0.034*
			(−2.13)	(−1.86)			(−1.78)	(−1.76)
Upstream Wetland Change (ha)		−0.071**				−0.059**		
		(−2.26)				(−2.08)		
Upstream Wetland Gain (ha)				−0.009				−0.009
				(−0.76)				(−0.73)
Upstream Wetland Loss (ha)				−0.075**				−0.060**
				(−2.48)				(−2.19)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,827	1,827	1,827	1,827	1,827	1,827	1,827	1,827

Table VII: Natural Capital Loss and Offering Yields

This table reports the difference-in-differences (DID) estimates with monthly county-level volume-weighted average municipal bond offering yields as dependent variables and extreme weather events as exogenous shocks. The event window extends for six years centered on the year of the extreme weather event. The sample in columns (1) and (2) includes all bonds. In columns (3) and (4), I split the sample into PADDD caused by subsistence and PADDD caused by all causes except subsistence. The Treated variable indicates municipal bonds of counties that experienced an extreme weather event and a PADDD event between $y-5$ and $y-1$ from the extreme weather event. Post is an indicator equal to one for observations occurring after the extreme weather event and zero otherwise. The control variables include county characteristics, municipal bond characteristics averaged at the county level, and the intensity of the weather event. The specifications include state-year-month and county fixed effects. The standard errors are clustered two ways by county and year-month. 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)	(4)
Treated × Post	0.075***	0.056***	0.043**	0.064***
	(3.56)	(3.17)	(2.53)	(3.93)
Treated × Post × Weather Exp.	0.038***	0.025***	0.016**	0.031***
	(3.25)	(2.93)	(2.64)	(3.36)
Sample	All	All	Subs.	No Subs.
Controls	Y	Y	Y	Y
State-Year-Month FE	Y	Y	Y	Y
County FE	N	Y	Y	Y
Observations	68,513	68,513	30,311	41,783
Adj. R^2	0.14	0.15	0.13	0.14

Table VIII: Subsample Tests and Event Window Robustness

This table reports the difference-in-differences (DID) estimates with monthly county-level and bond-level volume-weighted average municipal bond yields as dependent variables and extreme weather events as exogenous shocks. In Panel A, I report the results with an 11-month event window centered on the extreme weather event month. In Panel A, the sample in column (1) includes all bonds. Columns (2) and (3) include only revenue and general obligation bonds, respectively. In columns (4) and (5), I split the sample into PADDD caused by subsistence and PADDD caused by all causes except subsistence. In Panel B, I report the results with a seven-year event window centered on the extreme weather event month. In columns (1)-(3) and (4)-(6), the volume-weighted average yields are calculated at the county level and bond level, respectively. The Treated variable indicates municipal bonds of counties that experienced an extreme weather event and a PADDD event between $y-5$ and $y-1$ from the extreme weather event. Post is an indicator equal to one for observations occurring after the extreme weather event and zero otherwise. The control variables include county characteristics, municipal bond characteristics averaged at the county level, and the intensity of the weather event. In Panel A, the specifications include state-year-month and county fixed effects. In Panel B, the specifications include state-year and county fixed effects. The standard errors are clustered two ways by county and year-month. 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.

Panel A: 11-month Event Window

	(1)	(2)	(3)	(4)	(5)
Treated × Post	0.191***	0.292***	0.142**	0.142***	0.201***
	(3.35)	(3.08)	(2.13)	(2.63)	(3.43)
Treated × Post × Weather Exp.	0.180***	0.236***	0.138**	0.136***	0.194***
	(2.86)	(3.15)	(2.01)	(2.41)	(3.01)
Sample (Bonds, PADDD Cause)	All, All	Rev., All	GO, All	All, Subs.	All, No Subs.
Controls	Y	Y	Y	Y	Y
State-Year-Month FE	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y
Observations	77,161	43,814	57,953	56,128	38,551
Adj. R^2	0.12	0.14	0.11	0.11	0.13

Table VIII: Subsample Tests and Event Window Robustness - Continued

Panel B: 7-year Event Window

	County-Level			Bond-Level		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	0.155***	0.218***	0.123**	0.168***	0.235***	0.149***
	(3.18)	(2.89)	(2.18)	(3.03)	(2.86)	(2.58)
Treated × Post × Weather Exp.	0.163***	0.199***	0.119**	0.179***	0.203***	0.158***
	(2.72)	(3.15)	(2.08)	(2.68)	(3.04)	(2.61)
Sample (Bonds, PADDD Cause)	All, All	Rev, All	GO, All	All, All	Rev, All	GO, All
Controls	Y	Y	Y	Y	Y	Y
State-Year FE	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Observations	432,368	238,507	321,655	2,805,844	1,186,678	1,619,166
Adj. R^2	0.14	0.15	0.13	0.16	0.17	0.16

Internet Appendix for

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

I. Robustness Tests

A. Wetlands and Credit Ratings

It is possible that credit rating agencies also update their estimates of local risk after an extreme weather event. For this reason, I further explore the long-term implications of natural capital loss using municipal credit ratings and, specifically, the probability of rating downgrades. For this analysis, I use a linear probability model with an indicator variable that switches from zero to one after a rating downgrade as the dependent variable. The specifications are identical to the main analysis except for the dependent variable. In unreported results, I find that one standard deviation loss in upstream wetlands increases the likelihood of credit rating downgrading by 4.2%. This increase is equivalent to 23% of the sample average likelihood of rating downgrades (4.2%/17.88%).

B. Infrastructure vs. Non-Infrastructure Use of Proceeds

I exploit the heterogeneity in the bonds' use of proceeds to study the cross-sectional effect of natural capital. I hypothesize that bonds with infrastructure as use of proceeds are more exposed to nature loss risk since these bonds are directly tied to projects 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 infrastructure as use of proceeds.

To test this hypothesis, I classify bonds into infrastructure and non-infrastructure use of proceeds and compute two volume-weighted yield averages for each county at a monthly frequency:

one for the infrastructure bonds and one for the non-infrastructure bonds.[1] Then, I utilize the same approach described in Section III.E.4 and I add a triple interaction term between *Treated*, *Post*, and the infrastructure indicator. The results in Table IAVII column (1) show that the yield increase for bonds with infrastructure use of proceeds is 13 basis points more than non-infrastructure bonds.

For robustness, I estimate the cross-sectional effect of natural capital loss on bond yields using matching. Since municipal bonds trade infrequently, I aggregate the yields into a volume-weighted average for the pre- and post-period, respectively. Larger trades and trades executed closer to the event month receive greater weighting.[2] First, I restrict the matches to bonds issued in the same state with the same rating, type (general obligation or revenue), insurance status, county-level FEMA transfers indicator (i.e., below or above median FEMA transfers), and quintile of ratio of natural capital land area (protected area) to total county land area. 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 for the propensity score are as follows: bond coupon rate, county extreme weather exposure in the past five years, county elevation, distance from the coast, density, population, personal income, unemployment rate, debt-to-tax-revenue ratio, and trend in population. I estimate a DID regression model with bond yields as the dependent variable and the triple interaction between the treatment, the post, and the infrastructure indicators as the main independent variable of interest.[3] The coefficient of the triple interaction term represents the differential effect between bonds with infrastructure and non-infrastructure use of proceeds.

The final sample includes only the treated and the two matched control observations. The estimates in Table IAVII column (2) show that bonds with infrastructure as use of proceeds are more affected than the rest of the sample by 16 basis points. The results are qualitatively similar

[1] I exclude bonds that mention refunding for the use of proceeds since I do not have information that helps identify which bonds are being refunded.

[2] Similar to Robertson and Spiegel (2017), the weight is computed using the ratio of the squared root of the volume of the trade and the squared root of the time length between the trade and the event.

[3] The single indicators and the partial interactions are included in the DID model.

to the estimates without matching.

For additional robustness, following Crabbe and Turner (1995), Bernstein, Hughson, and Weidenmier (2019), Larcker and Watts (2020), and Schwert (2020), I estimate the effect of natural capital loss using 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. For example, in April 2011, Los Angeles County, CA, issued a municipal bond to fund a project on water utilities. In August of the same year, Los Angeles County, CA, also issued a bond with "pension" as use of proceeds.

It is plausible 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 IAVII 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 infrastructural bonds.

C. Political and Climate Change Beliefs

The local political and climate change beliefs might affect the response to natural capital loss and extreme weather events. To examine this possibility, I utilize the same approach as in Table VIII and add a triple-interaction term between the treatment, the post-extreme weather, and the Republican indicators. The Republican indicator equals one for counties where the percentage of votes for a Republican presidential candidate is above the sample median.[4] Also, I test the role of climate change beliefs using the 2014 Yale Climate Opinion Survey data to define the $Worried$ indicator. Specifically, I utilize the response to the following question: "How worried are you about global warming?" The $Worried$ indicator equals one for counties where the percentage

[4] I utilize the information on the county-level votes in presidential elections from the MIT Election Data + Science Lab (https://electionlab.mit.edu).

of respondents who state to be worried is greater than the median and zero otherwise.[5]

The results in Table IAVIII columns (2) and (3) show no significant difference between Republican and Democratic counties, as well as worried and not worried counties. Two phenomena might be at play. First, local governments in Republican (non-worried) counties might invest less in adaptation strategies (natural and non-natural), and, therefore, they suffer more from extreme weather damage.[6] Alternatively, local Republican (non-worried) investors may not believe in climate change. Consequently, these investors might ignore the increasing local climate change risk due to natural capital loss.

D. Time Trends in Climate Change Risk Pricing

Goldsmith-Pinkham et al. (2021) find that the municipal bond market starts pricing sea-level rise exposure around 2011. It is plausible that investors have become more aware of climate change risk in recent times and that the nature premium follows a similar trend. Following Goldsmith-Pinkham et al. (2021), I estimate the effect of nature loss before and after 2012. Specifically, the indicator $Post-2012$ equals one for the period after 2012 and zero otherwise. The results in Table IAVIII column (4) are consistent with Goldsmith-Pinkham et al. (2021) and show an increase in the nature premium after 2012 for both revenue and general obligation bonds.[7] Lastly, consistent with the literature, I find that bonds with longer maturities are more sensitive to climate change risk as well as the effect of natural capital loss (Table IAVIII column (5)).

E. De Chaisemartin and d'Haultfoeuille (2020) DID Approach

The presence of heterogeneous treatment effects could bias the estimates (Callaway and Sant'Anna (2021), Sun and Abraham (2021), Goodman-Bacon (2021), and De Chaisemartin and d'Haultfoeuille (2020)). For this reason, I compute the DID estimator proposed by De Chaisemartin and d'Haultfoeuille

[5]The possible responses are very worried, somewhat worried, not very worried, and not at all worried. I consider the first two responses as worried.

[6]County fixed effects at least partially account for unobservable adaptation strategies.

[7]Unreported results show that the adaptation premium does not decrease in states that have already experienced a PADDD event.

(2020) using the Stata package *did_multiplegt* and replicate the analysis in Section III.E.5. The results reported in Table IAIX are qualitatively similar to the results in Table V.

F. Placebo Test and State Exclusions

In addition to enacted PADDD events, the PADDD dataset contains proposed PADDDs. I utilize the proposed events to perform a placebo test using the difference-in-differences estimator presented in De Chaisemartin and d'Haultfoeuille (2020). Specifically, I repeat the analysis in Table VIII using the PADDD proposal to identify the treated counties. The results of the placebo test show that, after an extreme weather event, the difference between the counties in which a PADDD was proposed (treated group) and the control group is statistically indifferent from zero.[8] In addition, I repeat the analysis in Section III.E.5 and exclude one state at a time. The results are qualitatively similar when leaving one state out of the estimation.

G. Municipal Bond Credit Spread

Similar to Goldsmith-Pinkham et al. (2021), I repeat the analysis in Section III.E.5 using the municipal bond credit spread. In particular, I use the municipal bonds AAA-rated curve as a tax-exempt benchmark for the municipal bond credit spread analysis.[9] The outcome variable is the credit spread, which equals the bond yield minus the maturity-matched par yield from the AAA-rated curve. The results are reported in Table IAX and are qualitatively similar to the results in Section III.E.5. Further, the economic magnitude is comparable to the sea level rise exposure effect reported in Goldsmith-Pinkham et al. (2021).

[8] The coefficient of the Treated $\times$ Post interaction equals 0.008 (t-statistic$=$ 0.41).

[9] I collect the municipal bonds AAA-rated tax-exempt benchmark curve from 2005 to 2020 from Bloomberg.

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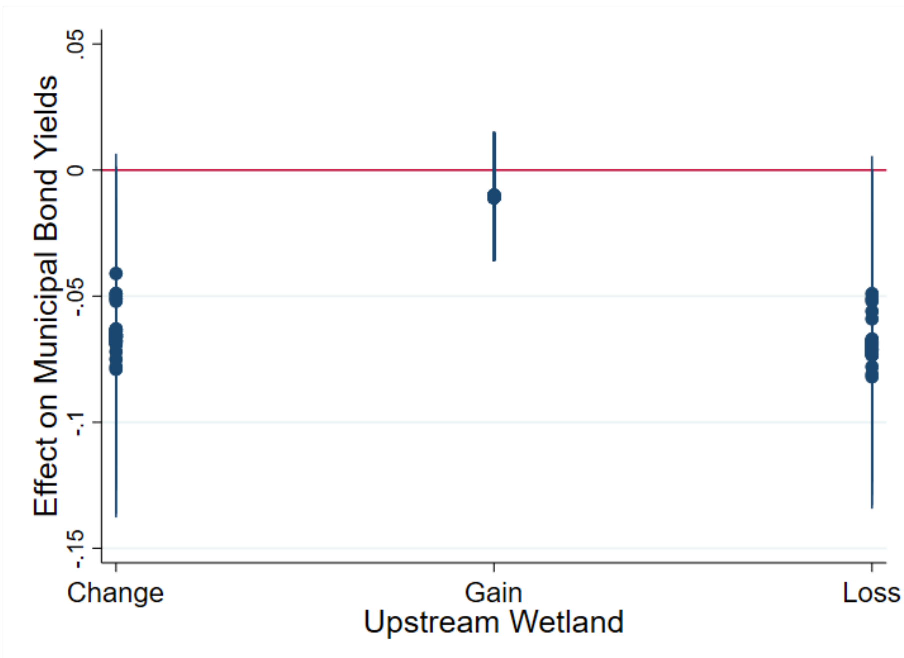

Figure IA1: Leave-one-out Sensitivity Analysis
This figure reports the leave-one-out estimation coefficients of the upstream-downstream difference-in-differences (DID) model. The estimations are run 49 times, each time excluding one state. The blue dots represent the coefficients of the upstream wetlands change, gain, and loss. The vertical lines represent 95% confidence bands.

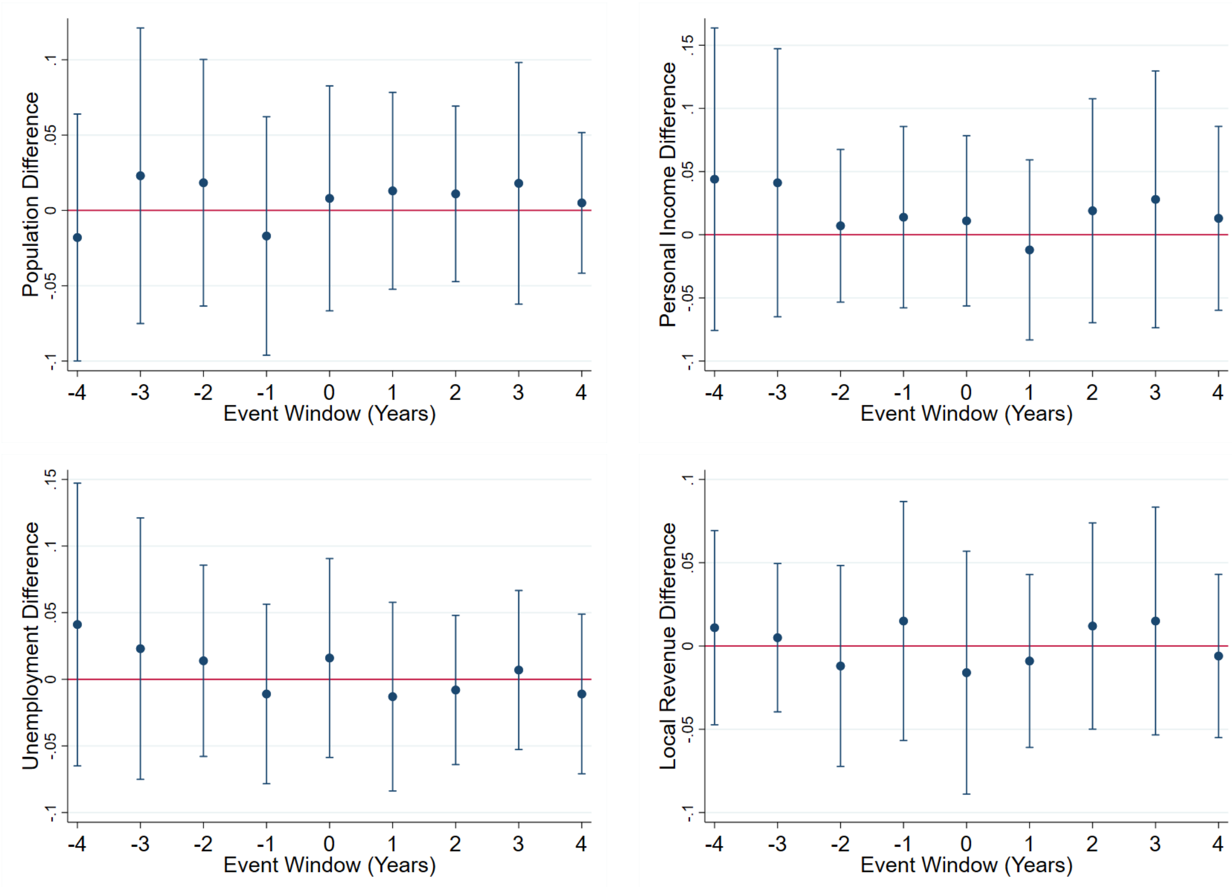

Figure IA2: Population, Income, Unemployment, and Local Revenue Trends
This figure reports the coefficients from the difference-in-differences (DID) estimates with selected county characteristics as dependent variables and PADDD as exogenous shocks. The coefficients reported are estimated using the same approach as eq. (6), except for the dependent variables, the use of year indicators, and the exclusion of bond characteristics. The dependent variables are changes in annual population, personal income, unemployment rate, and local revenue. The specifications include state-year and county fixed effects. The dots represent the coefficient estimate for the interaction between the treatment and the year indicators. The vertical lines represent 95% confidence bands. The sample period begins four years before the PADDD and ends four years after the PADDD. The standard errors are clustered two ways by county and year.

Table IAI: Bonds' Use of Proceeds Classification - Infrastructure vs Non-infrastructure

This table reports the use of proceeds utilized to classify bonds into "infrastructure" and "non-infrastructure." This information is collected from Bloomberg.

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

Table IAII: Definitions of PADDD Causes

This table reports the definition of the causes of PADDD as reported in the PADDD dataset (Conservation International and World Wildlife Fund (2021)) and Mascia, Sharon, and Roopa (2012).

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

Table IAIII: Natural Capital Loss and Bond Yields - Different Treatment Windows

This table reports the difference-in-differences (DID) estimates with monthly county-level volume-weighted average municipal bond yields as dependent variables and extreme weather events as exogenous shocks. I split the sample into pre- and post-extreme weather event periods. The sample in columns (1) and (4) includes all bonds. Columns (2) and (5) include only revenue bonds. Columns (3) and (6) include only general obligation bonds. The Treated variable indicates municipal bonds of counties that experienced an extreme weather event and a PADDD event between $y-7$ and $y-2$ (columns (1)-(3)) or $y-10$ to $y-2$ (columns (4)-(6)). Post is an indicator equal to one for observations occurring after the extreme weather event and zero otherwise. The control variables include county characteristics, municipal bond characteristics averaged at the county level, and the intensity of the weather event. The specifications include state-year-month and county fixed effects. The standard errors are clustered two ways by county and year-month. 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)	(4)	(5)	(6)
Treated × Post	0.198***	0.278***	0.153***	0.201***	0.276***	0.161**
	(3.15)	(3.31)	(2.58)	(3.17)	(3.38)	(2.28)
Treated × Post × Weath. Exp.	0.188***	0.211***	0.158***	0.173***	0.174***	0.159***
	(2.91)	(3.14)	(2.62)	(2.89)	(3.11)	(2.61)
Sample	All	Rev.	GO	All	Rev.	GO
Controls	Y	Y	Y	Y	Y	Y
State-Year-Month FE	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Treatment Window	$y-7$ to	$y-7$ to	$y-7$ to	$y-10$ to	$y-10$ to	$y-10$ to
	$y-2$	$y-2$	$y-2$	$y-2$	$y-2$	$y-2$
Observations	82,545	45,908	61,997	83,411	46,390	62,648
Adj. R^2	0.13	0.15	0.12	0.13	0.15	0.12

Table IAIV: Natural Capital Loss and Bond Yields - PADDD Event Study

This table reports the difference-in-differences (DID) estimates with monthly county-level volume-weighted average municipal bond yields in the secondary market (columns (1)-(3)) and in the primary market (columns (4)-(6)) as dependent variables and PADDD as exogenous shocks. The estimation window starts the year before PADDD and ends the year after it. The sample in columns (1) and (4) includes all bonds. Columns (2) and (5) include only revenue bonds. Columns (3) and (6) include only general obligation bonds. The Treated variable indicates municipal bonds of counties that experienced a PADDD event and zero otherwise. Post is an indicator equal to one for observations occurring after the PADDD event and zero otherwise. Extr. Weath. is an indicator equal to one for counties that experience precipitation greater than the 95^{th} percentile of the past local distribution. The control variables include county characteristics, municipal bond characteristics averaged at the county level, and the intensity of the weather event. The specifications include state-year-month and county fixed effects. The standard errors are clustered two ways by county and year-month. 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.

	Yields			Offering Yields		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	0.007	0.011	0.005	0.008	0.009	0.008
	(0.34)	(0.48)	(0.32)	(0.37)	(0.35)	(0.36)
Treated × Post × Extreme Weath.	0.173***	0.218***	0.143**	0.122***	0.139***	0.114***
	(2.78)	(3.22)	(2.01)	(2.63)	(2.97)	(2.28)
Sample	All	Rev.	GO	All	Rev.	GO
Controls	Y	Y	Y	Y	Y	Y
State-Year-Month FE	Y	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y	Y
Observations	121,285	68,144	90,091	54,136	26,321	32,912
Adj. R^2	0.14	0.15	0.14	0.14	0.15	0.14

Table IAV: Wetland Changes and Municipal Bond Yields - Flooded Counties

This table reports the long differences (LD) and upstream-downstream difference-in-differences (DID) estimates with county-level volume-weighted municipal bond yields in the secondary market (columns (1)-(4)) and in the primary market, i.e., offering yields (columns (5)-(8)) as dependent variables. The changes in the local wetland area are defined at the county level. The sample includes only counties that experienced flooding during the sample period. In columns (1), (2), (5), and (6), I model the response of bond yields and ratings to changes in wetlands area as linear. In columns (3), (4), (7), and (8), I allow for differential responses to gains and losses in wetlands areas. Upstream wetland changes are defined as changes in wetlands in all areas upstream of the county under consideration. The control variables include changes in county characteristics, municipal bond characteristics averaged at the county level, weather exposure, and total changes within each county's watershed (both upstream and downstream). The standard errors are clustered by county. 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.

Dependent Variables	Yield (b.p.)				Offering Yields (b.p.)			
	LD	DID	LD	DID	LD	DID	LD	DID
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Local Wetland Change (ha)	−0.041*	−0.033*			−0.039*	−0.031*		
	(−1.93)	(−1.77)			(−1.88)	(−1.67)		
Local Wetland Gain (ha)			−0.008	−0.008			−0.007	−0.008
			(−0.50)	(−0.51)			(−0.48)	(−0.45)
Local Wetland Loss (ha)			−0.044*	−0.042*			−0.043*	−0.041*
			(−1.90)	(−1.88)			(−1.89)	(−1.84)
Upstream Wetland Change (ha)		−0.065**				−0.063**		
		(−2.26)				(−2.21)		
Upstream Wetland Gain (ha)				−0.009				−0.008
				(−0.71)				(−0.72)
Upstream Wetland Loss (ha)				−0.071***				−0.068***
				(−2.78)				(−2.61)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1,118	1,118	1,118	1,118	1,118	1,118	1,118	1,118

Table IAVI: Natural Capital Loss and Bond Yields - Fixed Effects Robustness
This table reports the difference-in-differences (DID) estimates with monthly county-level and bond-level volume-weighted average municipal bond yields as dependent variables and extreme weather events as exogenous shocks. Each column includes different fixed effects specifications. In Panel A, I report the results with an 11-month event window centered on the extreme weather event month. In Panel B, I report the results with a seven-year event window centered on the extreme weather event month. In columns (1)-(3) and (4)-(6), the volume-weighted average yields are calculated at the county level and bond level, respectively. The Treated variable indicates municipal bonds of counties that experienced an extreme weather event and a PADDD event between $y-5$ and $y-1$ from the extreme weather event. Post is an indicator equal to one for observations occurring after the extreme weather event and zero otherwise. The control variables include county characteristics, municipal bond characteristics averaged at the county level, and the intensity of the weather event. The standard errors are clustered two ways by county and year-month. 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.

Panel A: 11-month Event Window

	(1)	(2)	(3)	(4)
Treated × Post	0.214***	0.211***	0.197***	0.193***
	(3.71)	(3.68)	(3.44)	(3.41)
Treated × Post × Weather Exp.	0.198***	0.196***	0.184***	0.182***
	(3.12)	(3.08)	(2.93)	(2.88)
Controls	Y	Y	Y	Y
State FE	Y	N	Y	N
State-Year FE	N	Y	N	Y
County FE	N	N	Y	Y
Observations	77,161	77,161	77,161	77,161
Adj. R^2	0.11	0.11	0.14	0.14

Table IAVI: Natural Capital Loss and Bond Yields - Fixed Effects Robustness - Continued

Panel B: 7-year Event Window

	County-Level			Bond-Level		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	0.165***	0.163***	0.157***	0.177***	0.176***	0.171***
	(3.71)	(3.59)	(3.22)	(3.11)	(3.09)	(3.08)
Treated × Post × Weather Exp.	0.171***	0.169***	0.164***	0.183***	0.184***	0.180***
	(2.86)	(2.81)	(2.74)	(2.71)	(2.74)	(2.71)
Controls	Y	Y	Y	Y	Y	Y
State FE	Y	N	Y	Y	N	Y
State-Year FE	N	Y	N	N	Y	N
County FE	N	N	Y	N	N	Y
Observations	432,368	432,368	432,368	2,805,844	2,805,844	2,805,844
Adj. R^2	0.11	0.11	0.14	0.11	0.11	0.16

Table IAVII: Natural Capital Loss and Bond Yields - Infrastructure vs Non-infrastructure Use of Proceeds

This table reports the difference-in-differences (DID) estimates with monthly volume-weighted average municipal bond yields as the dependent variable and extreme weather as exogenous shocks. Column (1) reports the regression estimates at the county level and columns (2) and (3) report the matching estimates at the bond level. The Treated variable indicates municipal bonds of counties that experienced an extreme weather event and a PADDD event between $y-5$ and $y-1$ from the extreme weather event. Post is an indicator equal to one for observations occurring after the extreme weather event and zero otherwise. Infrastructure indicates bonds with the use of proceeds classified as infrastructure. The control variables include county characteristics, municipal bond characteristics, and the intensity of the weather event. The specifications include state-year-month and county fixed effects. For column (2), the matches are restricted to bonds issued in the same state with the same rating, type (general obligation or revenue), insurance status, county FEMA transfers indicator (i.e., below or above median FEMA transfers), indicator for a disaster declaration in the previous five years, and quintile of the ratio of natural capital land area (protected area) to total county land area. I also allow a maximum of two years difference in maturity and a maximum of six months difference in the extreme weather event date. The variables used for the propensity score include coupon rate, Weather Exp.$_{1-5}$, county elevation, distance from the coast, density, population, personal income, unemployment rate, debt-to-tax-revenue ratio, and trend in population. For column (3), I match infrastructure and non-infrastructure bonds issued by the same county in the same year. The standard errors are clustered two ways by county and year-month 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	0.181***	0.208***	0.213***
	(3.11)	(3.07)	(3.36)
Treated × Post × Infrastructure	0.133***	0.157***	0.204***
	(3.02)	(3.31)	(3.59)
Matched Sample	N	Y	Y
County Controls	Y	Y	N
Bond Controls	Y	Y	N
Fixed Effects	Y	N	N
Same County	N	N	Y
Observations	81,052	2,614	418
Adj. R^2	0.15	0.21	0.22

Table IAVIII: Natural Capital Loss and Bond Yields - Farming, Politics, Climate Change Beliefs, and Time Trends

This table reports the difference-in-differences (DID) estimates with monthly county-level volume-weighted average municipal bond yields as the dependent variable and extreme weather as exogenous shocks. The Treated variable indicates municipal bonds of counties that experienced an extreme weather event and a PADDD event or are within a 25-mile radius between $y-5$ and $y-1$ from the extreme weather event. Post is an indicator equal to one for observations occurring after the extreme weather event and zero otherwise. Farming is an indicator equal to one if the county is classified as economically dependent on farming and zero otherwise. Republican is an indicator equal to one for counties where the percentage of votes for a Republican presidential candidate is above the median. Worried is an indicator equal to one for counties where the percentage of respondents who state to be worried is greater than the median and zero otherwise. Post-2012 is an indicator equal to one for observations occurring after 2012 and zero otherwise. Mat. > 10 yrs is an indicator equal to one for bonds with a maturity greater than ten years and zero otherwise. The control variables include county characteristics, municipal bond characteristics averaged at the county level, and the intensity of the weather event. The specifications include state-year-month and county fixed effects. The standard errors are clustered two ways by county and year-month. 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)	(4)	(5)
Treated × Post	0.151***	0.193***	0.193***	0.191***	0.191***
	(3.46)	(3.26)	(3.27)	(3.26)	(3.25)
Treated × Post × Farming	0.171***				
	(4.01)				
Treated × Post × Republican		0.021			
		(0.88)			
Treated × Post × Worried			−0.018		
			(−0.79)		
Treated × Post × Post-2012				0.092***	
				(2.86)	
Treated × Post × Mat. > 10 yrs					0.091**
					(2.13)
Controls	Y	Y	Y	Y	Y
State-Year-Month FE	Y	Y	Y	Y	Y
County FE	Y	Y	Y	Y	Y
Observations	77,161	77,161	77,161	77,161	77,161
Adj. R^2	0.15	0.12	0.12	0.14	0.14

Table IAIX: De Chaisemartin and d'Haultfoeuille (2020) Robustness Test
This table reports the difference-in-differences (DID) estimates using the De Chaisemartin and d'Haultfoeuille (2020) estimator with monthly county-level volume-weighted average municipal bond yields as dependent variables and extreme weather events as exogenous shocks. The sample in column (1) includes all bonds. Columns (2) and (3) include only revenue and general obligation bonds, respectively. The Treated variable indicates municipal bonds of counties that experienced an extreme weather event and a PADDD event between $y-5$ and $y-1$ from the extreme weather event. Weather Exp. represents the intensity of the precipitation event. Post is an indicator equal to one for observations occurring after the extreme weather event and zero otherwise. The control variables include county characteristics, municipal bond characteristics averaged at the county level, and the intensity of the weather event. The specifications include state-year-month and county fixed effects. The standard errors are clustered at the county 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	0.178***	0.262***	0.164***
	(2.82)	(3.25)	(2.48)
Treated × Post × Weather Exp.	0.188***	0.268***	0.141**
	(2.81)	(2.56)	(2.12)
Sample	All	Rev.	GO
Controls	Y	Y	Y
State-Year-Month FE	Y	Y	Y
County FE	Y	Y	Y
Observations	77,161	43,814	57,953
Adj. R^2	0.13	0.14	0.12

Table IAX: Natural Capital Loss and Bond Spreads - Extreme Weather Events
This table reports the difference-in-differences (DID) estimates with monthly county-level average volume-weighted municipal bond spreads as dependent variables and extreme weather events as exogenous shocks. The sample in column (1) includes all bonds. Columns (2) and (3) include only revenue and general obligation bonds, respectively. The Treated variable indicates municipal bonds of counties that experienced an extreme weather event and a PADDD event between $y-5$ and $y-1$ from the extreme weather event. The controls include county characteristics, municipal bond characteristics averaged at the county level, and the intensity of the weather event. The specifications include state-year-month and county fixed effects. The standard errors are clustered at the county 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)	−0.002	−0.003	−0.002
	(−0.38)	(−0.45)	(−0.81)
Treated × 1(Month −4)	0.002	−0.004	0.002
	(0.36)	(−0.45)	(0.52)
Treated × 1(Month −3)	0.003	0.005	0.003
	(0.48)	(0.57)	(0.52)
Treated × 1(Month −2)			
Treated × 1(Month −1)	0.004	0.005	0.004
	(0.45)	(0.61)	(0.39)
Treated × 1(Month 0)	0.046**	0.061***	0.044*
	(1.97)	(3.65)	(1.78)
Treated × 1(Month 1)	0.052***	0.059***	0.047***
	(3.29)	(3.37)	(3.16)
Treated × 1(Month 2)	0.058***	0.063***	0.051**
	(2.53)	(3.02)	(2.18)
Treated × 1(Month 3)	0.044***	0.049***	0.042***
	(2.91)	(3.12)	(2.76)
Treated × 1(Month 4)	0.016	0.018	0.013
	(1.41)	(1.49)	(1.51)
Treated × 1(Month 5)	0.057**	0.059**	0.053**
	(2.33)	(2.38)	(2.11)
Sample	All	Rev.	GO
Controls	Y	Y	Y
State-Year-Month FE	Y	Y	Y
County FE	Y	Y	Y
Observations	77,161	43,814	57,953
Adj. R^2	0.13	0.14	0.12