Municipal Finance and Biodiversity Conservation

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Abstract

We investigate the relationship between biodiversity and municipal finance. At the county level, municipalities experience higher borrowing costs due to increased biodiversity exposure, significantly affecting both intensive and extensive margins. A one-standard-deviation increase in biodiversity exposure raises municipal bond yields by 42.4 (63.3) basis points (bps) dependent on the ecological and economic controls, while the extensive margin of bond issuance decreases by 0.61%. Our analysis highlights pricing heterogeneity based on regional species protection awareness finding that species awareness facilitates to mitigate the financial cost. This economic mechanism is driven by the effect of biodiversity conservation over real estate market, reflected in enriched biodiversity and lower credit ratings. Utilizing the federal Endangered Species Act (ESA) as an exogenous shock, we causally identify that the observed pricing pattern results from stringent species protection policies.

Keywords: Biodiversity Finance, Municipal Bond, Green Awareness, Endangered Species Act
JEL Classification: G1, Q57, Q58

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1 Introduction

The global decline in biodiversity has emerged as a critical environmental issue, highlighting the urgent need for effective conservation strategies (Jaureguiberry et al., 2022; Mazor et al., 2018). At the first Earth Summit, world nations recognized that human activities were drastically reducing biodiversity and accelerating species and gene loss (Cardinale et al. (2012)). Recent United Nations reports reveal that human actions have introduced over 37,000 invasive species into biomes, contributing to 60% of species extinctions [1]. Additionally, land-use changes, particularly the conversion of forests to agricultural land, threaten over 85% of the 28,000 species at risk of extinction [2]. The worsening biodiversity crisis calls for urgent, multifaceted action. In response, the United Nations Biodiversity Conference (COP15) in December 2022 introduced a global biodiversity framework aimed at preventing species extinction (Chan et al., 2023). The framework prioritizes eliminating over-exploitation, pollution, and unsustainable agricultural practices while emphasizing the need to redirect financial flows toward sustainable investments and away from biodiversity-damaging activities [3].

Despite growing awareness of biodiversity's importance, significant gaps persist in the academic literature on the economic impacts of biodiversity conservation policies. This gap is particularly pronounced in the finance domain, where studies linking biodiversity policies to financial markets are scarce. These research limitations stem partly from the difficulty of disentangling the effects of biodiversity conservation policies from other confounding factors. As Potts et al. (2016) observe, biodiversity is influenced by multiple human activities—both directly and indirectly—through channels such as climate change, pollution, invasive species, and pesticide use. These complex interactions complicate the isolation of conservation policy impacts within financial market contexts

Our study addresses this research gap by examining the Endangered Species Act (ESA) in the United States and its critical habitat designations, widely regarded as one of the most significant global biodiversity conservation initiatives (Langpap

[1] United Nations News: https://www.unep.org/news-and-stories/story/five-drivers-nature-crisis

[2] United Nations News: https://www.unep.org/news-and-stories/press-release/our-global-food-system-primary-driver-biodiversity-loss

[3] United Nations News: https://www.unep.org/un-biodiversity-conference-cop-15

et al., 2018). Specifically, we investigate the relationship between regional biodiversity and local government financial costs, as reflected in municipal bond issuance. This approach is particularly relevant because critical habitat protections are federally designated but locally implemented. By analyzing municipal bond pricing, we quantify the economic impact of critical habitat protection, offering novel insights into the financial implications of biodiversity regulation for local governments. Notably, our focus on the municipal bond market allows us to estimate impacts through both discount rate and cash flow channels independently, providing a more comprehensive assessment compared to existing studies, which often rely on land transaction data (Ferris and Frank (2021a), Auffhammer et al. (2020)).

To capture biodiversity's impact on the municipal bond market, we construct a county-level biodiversity index. Drawing on Liang et al. (2020) and Scholes and Biggs (2005), we utilize the eBird dataset, a global citizen science initiative managed by the Cornell Lab of Ornithology (Sullivan et al., 2014), which contains over 1 billion bird observations as of 2023. Using this dataset, we develop key biodiversity metrics at the county level, categorizing species based on their conservation regulation status. Compared to alternative indices in prior studies, our measure provides distinct advantages due to its frequent updates and extensive coverage, enabling real-time tracking of biodiversity changes. Birds serve as effective ecosystem health indicators, occupying diverse ecological niches and responding rapidly to environmental shifts (Whelan et al., 2015; Sekercioglu et al., 2019; Frank and Sudarshan, 2023). Their sensitivity to ecological changes provides early warnings of biodiversity degradation and highlights potential regulatory pressures on municipalities.

Nevertheless, raw bird measures may be affected by endogeneity issues, such as imperfect detection and heterogeneity in observer expertise, including variability in birdwatching effort and species identification skills (Callaghan et al., 2017, 2021; Sauer and Link, 2011). Additionally, regions with larger populations or more observers are likely to report more bird observations. To address these issues, we adjust for birdwatching effort and detection probability by incorporating high-dimensional fixed effects and accounting for regional characteristics like observer endogeneity. This adjustment is conceptually aligned with the quasi-structural approach proposed by Lerner and Seru (2022) for addressing patent endogeneity using regression or machine learning techniques. Ultimately, we demonstrate that

our results are robust to various alternative bird biodiversity metrics. Our proposed measure offers a distinct perspective compared to traditional physical risk metrics, such as flooding risk in Giglio et al. (2021), or time-invariant biodiversity risk indices, as documented by Giglio et al. (2023).

Utilizing our biodiversity measure, we conduct rigorous experiments to explore the relationship between regional ecosystem, bird biodiversity, and municipal bond pricing. The research question is both challenging and intriguing due to the presence of competing hypotheses contingent upon investors' biodiversity awareness. On the one hand, consistent with economic literature on environmental regulation stringency Auffhammer et al. (2020),Auffhammer et al. (2020) and Fried (2018), properties subject to tightening critical habitat requirements may experience adverse economic effects. This suggests that areas with higher biodiversity could face increased costs or reduced economic activity, potentially impacting municipal bond pricing negatively. On the other hand, recent studies on sustainable investing Pástor et al. (2021),Pedersen et al. (2021) and Zhang (2023), indicate that investors with higher environmental awareness may accept lower risk compensation for "green" assets. This implies that municipalities with higher biodiversity exposure could potentially benefit from lower borrowing costs if investors value biodiversity conservation. Overall, the net effect of biodiversity on municipal bond pricing depends on the interplay between regulatory costs and investor preferences.

Our paper first documents a unique finding within the municipal market. For the local government with higher biodiversity exposure, the borrowing costs increased as investors demand higher risk premium to compensate for this exposure. This effect manifests in multiple dimensions of municipal debt issuance. Municipalities face higher borrowing costs for their debt issuance (intensive margin), while simultaneously experiencing a decrease in the overall volume of municipal bonds issued (extensive margin). This reduction in volume manifests both in the total amount issued and in the frequency of issuance. The patterns show with both statistical and economic significance at the county level. These findings implies a transition risk framework comparable to Bolton and Kacperczyk (2021), Bolton and Kacperczyk (2023) and Hsu et al. (2023) targeting at biodiversity protection.

Our paper also documents the potential heterogeneity pricing effect related to bird biodiversity. First, as recent studies by Pástor et al. (2021) and Zerbib (2019)

have shown that investors with green preference tends to have lower premium compared with their "brown" counterparts. We utilize data on petitions for proposing new species for protection and critical habitat designations at the regional level, as a measure of biodiversity preference, assuming that a higher call for protection implies greater biodiversity preservation awareness. Consistent with findings in both corporate bond and equity markets, we observe that municipal bonds issued in counties with higher biodiversity awareness experience a smaller impact of biodiversity exposure on yield. The finding aligns with Babina et al. (2021a), where municipal bond market has local bias due to the market segmentation of tax incentive. Overall, our proposed conceptual framework concentrates in local municipal bond market transaction with conservation awareness.

Second, we documents the heterogeneous effect of biodiversity exposure risk on different on municipal bond issuer type. We find that General Obligation (GO) bonds, which are backed by the full taxing power of the issuing government, exhibit lower financial costs compared to Revenue bonds, which are solely backed by project-specific revenues. Specifically, the increase in borrowing costs (intensive margin) associated with biodiversity exposure is statistically significantly lower for GO bonds than for Revenue bonds due to the debt sustainability. This evidence suggests that biodiversity exposure predominantly could affect municipal finances through project-specific revenue channels. Moreover, we analyze how biodiversity risk impacts the financial performance of various sectors within municipal bond issuances. Consistent with Bolton and Kacperczyk (2021), we find that bonds issued for projects in biodiversity-sensitive industries—such as water, energy, utilities, and electricity—display heightened sensitivity to biodiversity exposure compared to other sectors.

Third, our analysis suggests a significant relationship between bond maturity and sensitivity to biodiversity exposure. Consistent with Giglio et al. (2021)'s findings on climate risk, we find that long-term bonds (those with maturities exceeding 16 years, 1.37%) exhibit smaller sensitivity to this risk compared to short-term bonds (those with maturities less than 8 years, 1.45%). The low sensitivity of longer-maturity bonds to biodiversity exposure reflects investors' forward-looking optimism, suggesting they anticipate lower significant impacts of biodiversity loss and related regulatory changes over time, thus demanding lower compensation for extended exposure to these evolving risks.

To investigate the economic mechanisms underlying biodiversity exposure, we analyze several channels through which this risk may impact municipal finance. First, building on Cornaggia et al. (2018a), we examine the relationship between third-party credit ratings and biodiversity risk, given their importance to investors. Our analysis reveals that municipal bond credit ratings decline with higher biodiversity exposure, indicating that rating agencies factor this risk into their evaluations, thereby shaping investor perceptions of creditworthiness. Second, we assess the impact of biodiversity exposure on fundamental economic factors. Property prices—a key source of local government tax revenue (Goldsmith-Pinkham et al., 2023a)—decrease with increased biodiversity exposure, consistent with Auffhammer et al. (2020), who show that species protection acts can adversely affect local economies. Additionally, we observe lower average establishment-level employment in regions with higher biodiversity exposure. Collectively, these findings demonstrate that municipal financial responses to ecological risks are driven by housing and corporate sector reactions. The combined effects contribute to higher risk premiums for biodiversity-intensive debts.

While we address potential endogeneity issues in our bird biodiversity measures, the underlying drivers of the biodiversity index remain a challenge. Conceptually, the index may be endogenous to both cash flow risks (Thomas et al. (2024)) and transition risks (Bolton and Kacperczyk (2021)). To establish causality, we employ a canonical Difference-in-Differences (DiD) approach, leveraging the Endangered Species Act (ESA) as an exogenous shock. Our analysis identifies transition risks associated with species conservation as the primary driver of biodiversity exposure. By classifying U.S. counties into treatment and control groups based on the presence or absence of ESA-protected species, we exploit the quasi-experimental setting created by the ESA to strengthen causal inference.

Leveraging the ESA as an exogenous federal-level shock, we formulate our hypothesis as follows: counties affected by ESA regulations will experience tighter species protection compared to non-ESA counties, leading to changes in both ecological and economic outcomes. This hypothesis is grounded in existing literature. Melstrom (2021) and Ferris and Frank (2021a) document that ESA enforceability constrains firm management and affects property values. Concurrently, Czech and Krausman (2001), Greenwald et al. (2019), and Mothes et al. (2021) show that stringent ESA policies can improve biodiversity conditions.

The property values, as one of the main local government income source for taxation (Goldsmith-Pinkham et al. (2023b)), are reduced in forward-looking land use valuations due to potential business restrictions from environmental policies. Furthermore, Ferris and Frank (2021a) demonstrates that species protection can constrain regional economic development, particularly in the labor sector. Within these frameworks, we find that the fundamentals of regional ecosystem and economics change. The species protection exposed areas as treatment reduce the property price by -20,374.88 USD. The corresponding establishment-level employment of aggregate county on average descends by 3.41 jobs per company, which represents a decrease of 8.6% of the average employment level (39.47 jobs).The bird biodiversity, however, is improved by 0.15. Overall, our DiD design identifies a causal link between ESA implementation with ecosystem and economics fundamentals jointly.

As for the financial market, our identification assumption is built upon the efficiency of the rating regulation from CRA (Credit Rating Agency) and the investors' demand for ratings. As Cornaggia et al. (2018a), Opp et al. (2013) and Kliger and Sarig (2000) argue, even with coarse rating schemes on municipalities, the market investors still have high reliance on the ratings for risk perceptions. Consistently, we also find evidences on the fundamental side for both ecosystem and economic fundamentals. This indicates that investors perceive the risks and require a compensation for holding the risk exposed assets. However, for the investors with higher biodiversity preservation awareness, the risk compensation is acceptable at a lower premium (Pástor et al. (2021)). Overall, the financial market is hypothesized with the joint effect of heterogeneous investors, levels of biodiversity preservation awareness and effective information production agency.

Our analysis and results contribute to the literature in several key dimensions. First, from an agricultural and environmental perspective, our study bridges financial markets and ecological systems by incorporating the bird index, providing a unique connection between ecological fundamentals and financial market dynamics. For instance, Auffhammer et al. (2020) show that ESA regulations significantly reduce vacant land market values, while Melstrom (2021) document the negative effects of biodiversity protection on agricultural production. Similarly, Ferris and Frank (2021b) find higher unemployment rates linked to species protection laws. Expanding this literature, Giglio et al. (2024) introduce a production function inte-

grating biodiversity as an ecosystem component, finding that negative biodiversity news heightens national default risk through productivity channels. In contrast, our paper is the first to document the substantial borrowing costs municipalities face when financing biodiversity conservation efforts. We highlight the role of heterogeneous investor preferences in shaping financial responses to biodiversity policies, suggesting a structural economic framework that incorporates varying biodiversity demands among investors.

Our application of the bird biodiversity index also establishes a robust standard for biodiversity finance research, linking financial markets with granular ecological performance. While earlier studies address financial perspectives, their focus diverges. For example, Flammer et al. (2023) review biodiversity financing mechanisms such as private and blended finance channels, and Garel et al. (2023) explore biodiversity loss within equity markets, showing elevated forward-looking risks for firms with greater biodiversity loss, particularly post-COP15. Giglio et al. (2023) introduce a textual biodiversity risk metric, demonstrating that investors require risk premiums for holding biodiversity-exposed assets, while Giglio et al. (2024) integrate biodiversity into a production function framework to emphasize its ecosystem productivity role. Notably, Thomas et al. (2024) measure biodiversity using a bird index but focus on its relationship with earnings surprises rather than policy implications. In contrast, our study links financial markets directly to granular ecological changes, offering a novel perspective on the financial market dynamics shaped by historical biodiversity policies. This contribution underscores the unique financial implications of realized species conservation efforts.

With regard to the climate finance ESG literature, we contribute on a biodiversity perspective which is different from most climate finance literature and have insightful implications for greenness scheme of human beings. For instance, most of the papers on climate finance focus on different exogenous forces (Bolton and Kacperczyk (2021), Bolton and Kacperczyk (2023), Hsu et al. (2023), Giglio et al. (2021), Bansal et al. (2017), Kruttli et al. (2023), Ramadorai and Zeni (2024)). In sum, these papers focus on granular environmental risk and explore the risk implication over these securities. Our paper documents a granular county risk on biodiversity policy from municipal viewpoint.

In the context of green bond literature, Eskildsen et al. (2024) propose a method for estimating greenium in debt issuance using forward-looking expected returns,

while Zerbib (2019) document a negative bond greenium linked to third-party rating scores. Rossitto (2021) introduce a unique framework for green bond ownership, demonstrating its pricing implications through green premiums. In contrast, our paper focuses on biodiversity transition risk and highlights a premium driven by species protection regulations. The study most closely related to ours is Chen et al. (2024), which examines municipal green bonds in China's corporate bond market, characterized by significant liquidity frictions. However, their analysis offers limited insights into heterogeneous green effects or the mechanisms driving biodiversity-related financial impacts in the U.S. market. Our study diverges by emphasizing the persistent relationship between bird biodiversity and municipal finance in the U.S., rather than focusing solely on discrete species protection shocks. Leveraging detailed data on property values and establishments, we identify specific economic channels through which realized biodiversity policies influence municipal financing. This approach offers a richer understanding of biodiversity's financial implications within the U.S. context.

Finally, our paper also contributes to empirical with identification of biodiversity regulation effect and closely connect it financial market by tracking the ESA historical shocks. As far as we know, there is few paper tackling this empirical finance question up to now, even though there are close papers on economics emphasizing the identification on ESA policies(Melstrom (2021),Ferris and Frank (2021a) and Ferris and Frank (2021a)). From this perspective, our paper shows consistent evidence from the financial market and emphasizes the potential financial friction for municipalities in financing species conservation.

The structure of paper is shown as the following. In section 2, we introduce the most important settings of our paper about bird biodiversity and ESA (endangered species protection). Section 3 formalizes the conceptual framework of our empirical work and hypothesis. Section 4 goes through the main data and summary of statistics. Then, in section 5, 5.1, we show our most important main results with heterogeneous effect. In section 5.2, the paper discusses the identification strategy with ESA shocks and identify the exogeneity for biodiversity exposure exposure.

2 Endangered Species Act

2.1 Endangered Species Act (ESA) and Critical Habitat Designation

The Endangered Species Act (ESA) of 1973 stands as the cornerstone federal law in the United States designed to protect endangered species and their habitats. Building upon earlier legislation like the Endangered Species Preservation Act of 1966, the ESA has recognized the critical importance of habitat conservation since its inception (Czech and Krausman, 2001). The Act has proven to be a powerful tool for conservation, with studies showing that it has prevented the extinction of 99 percent of the species it protects (Greenwald et al., 2019). Moreover, many species have shown significant recovery under its protection, including iconic examples like the bald eagle, grizzly bear, and humpback whale (Mothes et al., 2021).

The Endangered Species Act (ESA) establishes a comprehensive framework for protecting threatened and endangered species, with implications that extend across both public and private sectors. At its core, the ESA requires the listing of species as threatened or endangered based on scientific criteria, with habitat loss being a primary consideration. The implementation of the ESA involves two main components: the assessment and listing process, and the designation of critical habitat. The first consideration for listing a species is whether it faces “present or threatened destruction, modification, or curtailment of its habitat or range”. This assessment process includes conducting evaluations for each proposed species, proposing the listing or delisting or species, and identifying and reporting the current spatial range of each proposed species. Once a species is listed, Section 9 of the ESA prohibits any action that causes "take" of that species, broadly defined to include harming, harassing, or modifying habitat in a way that harms the species. This prohibition applies universally to all parties, including private businesses and public sectors, potentially restricting a wide range of activities.

Concurrently with the listing of a species, Section 4 of the ESA requires the designation of the species’ "critical habitat". This is considered the most stringent regulatory instrument within the ESA (Langpap et al., 2018). Critical habitat refers to specific geographical areas determined by the U.S. Fish and Wildlife Service (FWS) that are essential to the conservation of a listed species and may require spe-

cial management and protection. The designation occurs "on the basis of the best scientific data available and after taking into consideration the economic impact, and any other relevant impact". This listing process and critical habitat designation initiate a series of protective measures that can significantly impact land use and development activities across both public and private sectors (Auffhammer et al., 2020).

The enforcement of the ESA primarily falls under federal jurisdiction, with the U.S. Fish and Wildlife Service and NOAA Fisheries (for marine species) taking the lead. Recent reviews indicate that federal expenditures on the conservation of federally listed species make up approximately 95% of total ESA spending (Mothes et al., 2021). However, state and local governments may play important supporting roles in implementation and enforcement as well. The stringency of enforcement can vary across states, with some, like California, having additional state-level requirements triggered by critical habitat designations under laws such as the California Environmental Quality Act (CEQA).

The ESA's regulations can substantially impact local government finances and, by extension, municipal bond markets in several interconnected ways. Compliance with ESA requirements often necessitates increased expenditures on conservation efforts, habitat protection, and species management programs, which can strain municipal budgets and potentially affect the ability to fund other public services or repay bond obligations (Ferraro et al., 2007). Simultaneously, these regulations can influence local economic activities and tax revenues. Restrictions on land use due to critical habitat designations may limit development opportunities, potentially reducing property values and associated tax revenues (Auffhammer et al., 2020; Zabel and Paterson, 2006). However, some communities may experience economic benefits from increased tourism or recreational activities related to protected species habitats (Richardson and Loomis, 2009).

The Act's long-term influence on land use patterns and economic development strategies can have significant effects on a community's fiscal health, a crucial factor in municipal bond performance (Sunding and Terhorst, 2014; Quigley and Swoboda, 2007). While Section 10 of the ESA provides some flexibility through incidental take permits and Habitat Conservation Plans (HCPs), the costs of developing and implementing these plans can be substantial for local governments, further impacting their financial positions (Langpap et al., 2018). Consequently,

ESA-related expenditures and potential impacts on local tax bases can affect a municipality's ability to meet its debt obligations. These financial implications are particularly relevant when assessing municipal bond risks and returns, especially in areas with significant biodiversity or protected species habitats. Investors and financial analysts need to consider how ESA regulations might affect a municipality's fiscal health, both in the short and long term (Giglio et al. (2021),Painter (2020)). The complex interplay between conservation efforts, economic development, and municipal finance underscores the importance of a nuanced understanding of the ESA's impact on local government finances and, consequently, on municipal bond markets (Kiewiet and McCubbins (2014),Marlowe (2015)).

3 Conceptual Framework

We establish conceptual foundations for a hypothetical framework exploring the potential impact of biodiversity exposure on municipal bond pricing. This paper emphasizes key economic channels through credit rating agencies and local economies. In this economy, municipalities finance government spending, such as biodiversity recovery and sustainability initiatives, by issuing debt instruments as a form of blended capital funding (Flammer et al. (2023)). Investors hold these assets and perceive biodiversity transition signals as a source of risk. Given the necessity for regional governments to sustain their fiscal budgets and maintain ecosystems through tightening policies, their economies are unavoidably affected, causing deviations in revenues or growth from the laissez-faire economy.

Municipalities play a crucial role in financing and regulating biodiversity conservation in accordance with federal legislation, such as the Endangered Species Act (ESA) (Czech and Krausman (2001); Greenwald et al. (2019); Mothes et al. (2021)). To support endangered species recovery, local governments secure funding from both private and blended capital finance, as documented by Flammer et al. (2023). Consequently, the regional government issues municipal bonds, serving as one of the primary channels for blended capital. Market participants allocate their assets to projects based on either pecuniary or non-pecuniary benefits derived from municipal bonds.

Our first hypothesis examines the enforceability of the ESA on economic and ecological systems. Various economic studies debate the effectiveness of endan-

gered species protection. For instance, Melstrom (2021) finds that ESA implementation decreases property values in the transaction market due to species protection enforcement. Additionally, Ferris and Frank (2021a) shows that firms reduce labor hiring in response to stricter endangered species regulations. Conversely, the efficiency of ESA enforcement remains controversial. ESA (2002) questions the impact of ESA implementation, while ESA (2005) highlights potential failures due to limited on-the-ground conservation actions. Our first assumption posits that the ESA's effectiveness, through stringent biodiversity protection policies, can enhance endangered species recovery while imposing stricter land use restrictions on firm management.

Additionally, we hypothesize that biodiversity conservation may strain public finances, potentially crowding out sustainable funding within local government budgets. This assumption is grounded in Stokstad (2005) and Cardinale et al. (2012), which highlight the significant costs associated with biodiversity conservation, including the listing of endangered species and compensating landowners for vetoed developments. Both implicit and explicit government spending on conservation could, therefore, impact the sustainability of public finances.

Moreover, despite the enforceability of biodiversity protection, there remains controversy regarding how investors perceive these risks. Cornaggia et al. (2018a) provides compelling evidence that market investors heavily rely on credit rating agencies. This argument is further supported by structural models in Cornaggia et al. (2018b), which indicate that rating regulations significantly impact marginal investors. Conversely, Kisgen (2012) and Almeida et al. (2017) challenge these claims, suggesting that over-reliance on credit ratings may lead investors to erroneously reduce their investments. Overall, the underlying assumption for our empirical analysis is not solely based on the fundamental effects on ecology and economics, but also on how investors perceive these uncertainties through the informative signals provided by rating agencies.

Another critical question is whether investors exhibit heterogeneous preferences for biodiversity demands. According to Pástor et al. (2021) and Pedersen et al. (2021), investors with green preferences accept lower risk compensation for biodiversity exposure-exposed assets, balancing non-pecuniary benefits and risk premiums. Additionally, accounting for municipal bond market segmentation due to local investor taxation (Babina et al. (2021b)), premiums should be lower in re-

gions with higher biodiversity conservation awareness.

Finally, our assumption regarding biodiversity exposure considers the materialization of perceived risk for investors. Similar to climate change risk (Barnett et al. (2020)), biodiversity exposure encompasses uncertainties such as disaster risk, technical uncertainty, and forward-looking policy uncertainty. Consistent with Painter (2020), we hypothesize that municipal bonds with longer maturities may be riskier and command higher premiums due to the instantaneous realization of policy uncertainties. Conversely, Giglio et al. (2021) argues that forward-looking investments can mitigate yields on debts, suggesting that municipal bonds with longer maturities may have lower premiums.

4 Data

We establish our empirical analysis with diverse data sources. First, following Liang et al. (2020), we use the bird biodiversity proxy as a measure for realized granular ecosystems. Then, we integrate the bird biodiversity with the municipal bond pricing data from SDC Platinum WRDS and explore the municipal bond pricing to the bird biodiversity changes. To control the county-level confounding variables, we refer to the Bu and exploit the NETS (National Establishment Time Series) to construct county-level economic fundamentals. Finally, we complement our county-level data with BEA (Burea of Economic Agency) and US census characteristics to rule out alternative confounding interpretations.

Measures of Bird Biodiversity .

The bird biodiversity measures in this study are constructed based on the eBird dataset, a comprehensive, global citizen science initiative managed by the Cornell Lab of Ornithology (Sullivan et al., 2014). This comprehensive dataset comprises standardized "checklists" submitted by volunteer birdwatchers, detailing species, counts, location, and time of bird observations. Each checklist represents a unique birding event, recorded via GPS-enabled mobile applications or web interfaces. The eBird dataset has been widely used in ecological research, conservation biology, and interdisciplinary studies (La Sorte et al., 2017; Horns et al., 2018; Liang et al., 2020), offering a rich resource for biodiversity analysis. A detailed description of the eBird data and collection process can be found in Appendix C.

For our analysis, we used the entire eBird basic dataset (version ebd_relJul-2023), which includes all the records (over 37 million) spanning from the project's inception in 2002 to July 2023. We focused specifically on "complete" checklists, where observers confirm they are submitting a comprehensive list of all birds seen and/or heard during their observation period. We also restricted our sample to checklists marked with either "stationary" or "traveling" protocols, as these provide precise information on start time, duration, and distance covered during the observation. By using complete checklists, we can more accurately assess species presence and absence across different habitats and time periods. To further ensure data quality and minimize potential biases, we employed an additional set of filtering criteria, following established scientific practices (Callaghan et al., 2017, 2021; Cazalis et al., 2020). We only included complete checklists with a duration greater than 5 minutes and less than 600 minutes (10 hours), and which covered a traveled distance of less than 10 km. These filters aim to remove potential "outliers" which could skew our dataset and subsequent analyses. The duration filter helps to exclude very brief observations that might not provide a comprehensive picture of the local avifauna, as well as extremely long observations that might introduce other biases. The distance filter ensures that the observations are relatively localized, reducing the risk of including multiple distinct habitats within a single checklist. However, it's important to note that even with these rigorous filtering and quality control measures, some potential mistakes or inconsistencies are still possible in the eBird dataset, arising from factors such as species misidentification or data entry errors.

We calculate several biodiversity measures using species-level information from the eBird database, following methods proposed in the biodiversity literature (Polasky et al., 2005; Sauer et al., 2017; Rosenberg et al., 2019). Our main focus is on two key metrics: abundance and species richness. The abundance index counts the total number of individual birds observed each year, while the species richness index measures the number of distinct species recorded annually. These metrics provide a straightforward assessment of biodiversity, regardless of changes in individual species distribution or community composition over time. We chose to prioritize these measures in our main specification due to their interpretability and relevance to the scope of this paper. We then group bird species into two main categories based on their conservation status: endangered and non-endangered species. This

categorization is determined by whether a bird species has been listed on the endangered bird species listing, which serves as an indicator of the species' scarcity, and therefore the regulation relevance of the change in corresponding bird biodiversity measures.

Figure 1 displays the regional distribution of bird diversity across US counties. From the view of cross-regions, the western states, particularly California, exhibit higher biodiversity than most eastern areas. Notably, some middle regions like North Dakota also show high bird biodiversity due to their extensive protected areas and diverse habitats[4].In addition , we also plot the changes of bird biodiversity across regions through time in Appendix. Even though the counties with bird biodiversity shift over time, some of areas close to California have significant higher bird biodiversity than alternatives. The regions close to the east coast cities like New York also have higher densities of bird biodiversity compared with others. This cross-region might be attributed to the economics of regional areas and indicates a severe endogenous issue for bird biodiversity.

In Appendix, we provide the summary statistics for the biodiversity. We have a universe of bird biodiversity measures across US regions from 2002 to 2022. We calculate the standard deviation across regions within the US. The figure shows a clear upward trend indicating that the measure has a clear divergence within the US. This upward pattern implies that our proposed measure is sensitive to capture short-term biodiversity changes through time. In contrast to Giglio et al. (2021) focusing on the infrequent surveyed data like marine life to capture biodiversity, our proposed measure shows flexibility in estimating the ecosystem.

Municipal Bond .

We collect Securities Data Company's (SDC) Global Public Finance U.S. New Issues database for municipal bond issuance. SDC contains all the necessary municipal bond characteristics within the US including the issuer, issue date, issuer type, credit rating agency, issue size, yield to maturity, coupon rate, maturity date, etc.Finally, our sample includes 1,919,937 both GO (general obligation) bonds and Revenue bonds from January 1, 1980, to May 3, 2024. After merging with our bird observation data and winsorizing by replacing the top 1% and bottom 1%

[4]For instance, North Dakota features 5 national parks, 5 state forests, 63 national wildlife refuges, 3 national grasslands, and 13 state parks. Source: https://www.birdadvisors.com/backyard-birds-north-dakota/

of values with the 1% threshold, we retain 463,739 bonds in total from January 1, 2002, to December 31, 2022.Our final sample contains all types of issuers, including state governments, city governments, county governments, local school districts, public utility agencies, government-affiliated entities, and special purpose entities such as public transportation authorities, hospital authorities, housing authorities, and utility companies, as well as government-sponsored enterprises (GSEs).The majority of bonds are from taxable municipal samples, with 60,098 from the tax-exempted bonds.

Table 3 shows the summary of statistics for the municipal bond. On average, the sample ranges from 2002 to 2022. We conduct quantile analysis for municipal bond assets and explore some preliminary correlations between county-level biodiversity exposure and local economic fundamentals. As regional biodiversity exposure goes, there are lots of monotonic increasing county-level fundamentals including ecological confounding variables (water area, land area) and economic variables (GDP in Dollars, employment, personal income). This monotonic relationship implies endogenous concerns in identifying the effect of biodiversity over municipal financing.

County-Level Economics .

To control the county-level economic fundamentals, we collect the confounding variables from multiple data sources. Our first data source is from BEA (Bureau of Economic Analysis). We obtain all the county-level characteristics, including the ecological GDP, personal income, and employment ratio, in Table 3. The reason for us to include these variables is because of the endogeneity for bird biodiversity. This endogeneity might come from economics since it's intuitively acceptable to assume that counties with higher economics are more likely to track bird footprints with advanced infrastructure. Moreover, in order to rule out the potential impact of physical climate risk on the bird biodiversity index, we first download the flooding risk data from Giglio et al. (2021). We retrieve their flooding zones variables across regions at the county level as a proxy for flooding or sea level physical risk in Goldsmith-Pinkham et al. (2023b). Second, since the bird index area is closely connected with ecological variables, we obtain the data on water area and land area from US census to control the natural resource-related variations. Finally, we also compensate our database with NETS (National Establishment Time-Series) to

calculate the establishment-level employment ratio for counties.

Critical Habitat Designations .

Our study utilizes data on critical habitat designations under the Endangered Species Act (ESA), obtained from the U.S. Fish and Wildlife Service (USFWS). This agency is responsible for designating and managing critical habitats for threatened and endangered species. We collected spatial data in the form of shapefiles from the USFWS's Environmental Conservation Online System (ECOS) GIS data portal. These shapefiles delineate the geographic areas containing features essential to the conservation of listed species. In addition to the spatial data, we gathered information on the listed species associated with each critical habitat designation, including the species' common and scientific names, their listing status (threatened or endangered), and the date of critical habitat designation.

To integrate this information into our county-level analysis, we considered a county as 'treated' if any portion of a designated critical habitat intersected with the county's boundaries. The treatment timing for each affected county was set to the establishment date of the intersecting critical habitat. Counties that never intersected with any critical habitat designations or before the establishment date of critical habitat designation during our study period were categorized as control counties. This approach allows us to compare biodiversity and financial outcomes in treated counties (those with critical habitat designations) to control counties before and after the designation dates.

Our study uses data on critical habitat designations under the Endangered Species Act (ESA) from the U.S. Fish and Wildlife Service (USFWS), which manages these habitats for threatened and endangered species. We collected spatial data as shapefiles from the USFWS's Environmental Conservation Online System (ECOS) GIS data portal. These shapefiles delineate geographic areas essential for the conservation of listed species. Additionally, we gathered information on each species associated with these critical habitats, including their common and scientific names, listing status (threatened or endangered), and the date of habitat designation.

For our county-level analysis, a county was considered 'treated' if any designated critical habitat intersected its boundaries. The treatment timing was set to the date of the intersecting habitat's designation. Counties that never intersected

with any critical habitats during our study period or only did so before the designation dates were categorized as control counties. This method allows us to compare biodiversity and financial outcomes in treated counties to those in control counties before and after the designation dates.

We identified exogenous species protection risks using ESA implementation data from the USFWS. Following the establishment of the National Environmental Policy Act (NEPA) in 1970, there was a significant increase in the number of protected species, as illustrated in Figure 2. This trend is especially noticeable during our sample period from 2002 to 2022, reflecting the increased focus on species protection under the ESA in the United States.

Biodiversity Awareness .

The effectiveness of biodiversity-related regulations, such as the Endangered Species Act (ESA), is heavily influenced by public awareness and support for conservation efforts (Langpap et al., 2018). It is well recognized in ecological and conservation literature that the conservation capacity of ESA policy varies across regions, largely due to differences in local awareness and support (Mothes et al., 2021). Identifying hotspots of higher biodiversity awareness can help disentangle the heterogeneous effects of biodiversity policy regulations on local economics and municipal finances. This awareness can influence local land-use decisions, development practices, and even voter behavior. Therefore, areas with greater biodiversity awareness may experience reduced financial frictions in implementing or enhancing listing decisions and critical habitat designations.

To proxy for biodiversity awareness, we utilize data on ESA listing petitions. Petitions are formal requests to list or delist species under the ESA, typically initiated by environmental groups or other interest groups (brosi and biber 2012). These petitions serve as a form of political activity that lends time and legitimacy to conservation causes, which reflects a community's proactive stance on conservation [5].The frequency and nature of these petitions in a given area can provide insights into the local balance between conservation priorities and economic de-

[5]Petitions for listing are usually proposed by environmental groups seeking more stringent regulations for specific species or regions, while delisting requests often come from diverse interests and may be influenced by non-scientific factors. The ESA takes these petitions seriously, as many evolve into formal lawsuits and ultimately lead to settlements that shape policy outcomes(Langpap et al., 2018)

velopment concerns. By analyzing the geographic distribution of petitions, we can gauge regional variations in biodiversity awareness and its potential influence on local government decision-making and economic planning, potentially explaining why some communities adapt more readily to conservation requirements while others experience greater economic challenges.

We collect all petition reports from the FWS website, identifying mentioned bird species and their associated states. For each petition, we record submission times and categorize its purpose, distinguishing between 'Reclassify' petitions (downlisting to threatened or uplisting to endangered status) and 'APA' (Administrative Procedure Act) related petitions. The latter includes actions such as revising recovery plans, promulgating new 4(d) rules, designating experimental populations, and critical habitats. We calculate the frequency of these categorized petitions for each state-year-month combination, reflecting the intensity of conservation-related activities in each location over time. This granular temporal and spatial data tracks changes in biodiversity awareness across regions and periods, providing a nuanced measure of local interest in biodiversity issues. This measure serves as a proxy for biodiversity awareness in our subsequent analyses of conservation efforts and municipal financial outcomes. A detailed description of the petition categorization process and data construction can be found in Appendix B.2.

5 Empirical Analysis

5.1 Main Result

In this section, we first conduct empirical analysis to reveal the relationship between the municipal bond and bird biodiversity index. First, we explore their intensive relation by regressing the municipal bond yield (spread) over the bird biodiversity directly. Then, we focus on exploring the extensive margin of financial cost with regional bird biodiversity. Finally, we investigate the heterogeneous characteristics of municipal bond in response to the biodiversity exposure. The heterogeneous structure comes from issuers, investors and term structure for transition risk materialization correspondingly.

5.1.1 Intensive Margin

To assess the comprehensive impact of biodiversity on municipal finance, we conduct the following regressions as our result for intensive margins of biodiversity exposure over local government borrowing cost:

$$yield_{i,t} = \beta_0 Biodiversity_{i,t} + Control_{i,t} + \delta_i + \delta_t + \epsilon_{i,t}$$

We first regress the bond yield in the county i at time t on the bird biodiversity in the county i at time t. In the Table 5, columns (1) and (2) display the main results for municipal borrowing cost at the intensive margins. The bond yield is robust against whether we control endogenous variables including ecological and economic confounding variables. One standard deviation increase in the $Biodiversity_{i,t}$ contributes to 42.4 bps[6] (63.3 bps) increment in the bond yield with statistical significance. It's considered of great economic magnitude which is equal to 4.2% (6.4%) increase in the average bond yield of the full sample. This finding parallels to the empirical facts documented in Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2023) where they documents carbon transition risk; however, regarding the municipalities, investors perceive biodiversity exposure and require risk compensation with higher premiums.

Further, due to the investors' reliance on rating scores documented in Cornaggia et al. (2018a) and Opp et al. (2013), we estimate the corresponding credit ratings from Moody to explore whether credit rating agency disclose these biodiversity exposure or not. We design the following regressions:

$$Rating_{i,t} = \beta_0 Biodiversity_{i,t} + Control_{i,t} + \delta_i + \delta_t + \epsilon_{i,t}$$

Columns (3) and (4) in Table 5 report the results for credit ratings in response to biodiversity exposure. $Rating_{i,t}$ denotes the credit rating for security i at time t. With one standard deviation increase in the biodiversity exposure, the corresponding credit ratings from decrease by 11.2% (11.3%) conditional on whether we control the ecological and economic characteristics or not. The final result shows with statistical significance, even though the economic magnitude is relative not that large. Overall, we conclude that investors perceive the biodiversity exposure following the credit rating scores. Due to the downward credit rating, we find that the credit risks are higher for investors to hold the municipal assets. Therefore, investors

[6]basis points

would like to require a risk compensation for holding these assets.

5.1.2 Extensive Margin

Given the intensive marginal change of market pricing (*yield*), we explore the extensive marigin on the municipal borrowing cost in response to the biodiversity exposure with:

$$Y_{i,t} = \beta_0 Biodiversity_{i,t} + Control_{i,t} + \delta_i + \delta_t + \epsilon_{i,t}$$

$Y_{i,t}$ refers to variables on extensive margin for municipal financing, including total amount of bond issuance and probability of municipal financing. In addition, as one of the essential financing for municipalities, we also investigate the GO (general obligation) bonds for financing with the same variables. Table 6 discloses our main results on extensive margin for municipal bond pricing. Column (1) and (2) explore the issuance of the municipal bond. With one standard deviation change in biodiversity, the amount of total issuance reduces by 2.68. This is equivalent to 1.64% of the total issuance in the local economics. For the probability of total municipal bond issuance, a one standard deviation increase contributes to 0.61% drop of the probability for municipal bond issuance. This estimation is considered of great economic magnitude since it's equivalent to 2.89% reduction in the total issuance of the bond over the market. Overall, our paper shows that the biodiversity exposure not only improves the financial borrowing cost for municipalities but also it cuts down the equilibrium of the market realized on biodiversity finance through blended capital.

5.1.3 Alternative Biodiversity

Our main findings from both the intensive and extensive margins of the municipal bond market indicate significant relationships. However, Giglio et al. (2024) suggests that relationships between different dimensions of biodiversity may overlap. Giglio et al. (2023) proposed several alternative measures to gauge regional biodiversity, including economic-driven biodiversity(Gdp_Bio), labor-driven biodiversity (Emp_Bio), and area-based biodiversity ($Area_Bio$), and species-based biodiversity($Species_Bio$). Although some of these measures, like $Species_Bio$, show only cross-sectional variation and cannot change dynamically, they raise concerns about potential overlap with our findings on bird biodiversity.To address this con-

cern, we conducted regressions of municipal bond yield and Moody's ratings on these potential confounding variables:

$$\begin{aligned} Rating_{i,t} = \beta_0 Biodiversity_{i,t} + \beta_1 Emp_Bio_{i,t} + \beta_2 GDP_Bio_{i,t} + \beta_3 Area_Bio_{i,t} \\ + \beta_4 Species_Bio_{i,t} + Control + \delta_{c(i),t} + \epsilon_{i,t} \end{aligned} \quad (1)$$

$$\begin{aligned} Yield_{i,t} = \beta_0 Biodiversity_{i,t} + \beta_1 Emp_Bio_{i,t} + \beta_2 GDP_Bio_{i,t} + \beta_3 Area_Bio_{i,t} \\ + \beta_4 Species_Bio_{i,t} + Control + \delta_{c(i),t} + \epsilon_{i,t} \end{aligned}$$

Table 7 presents the main results, showing that even after controlling for these alternative biodiversity measures, bird biodiversity still has a statistically significant effect on municipal bond premiums. A one standard deviation increase (0.83) in biodiversity is associated with a 1.73% increase in municipal bond yield, which is substantial given the sample's average yield of 9.87%. Similarly, biodiversity significantly affects ratings, with a one standard deviation change associated with a 0.64-point decrease in Moody's ratings, equivalent to 3.5% of the average rating.Overall, even with these controls, the relationship between bird biodiversity and municipal bond yield remains robust. This suggests that our biodiversity measure captures a distinct dimension compared to those proposed by Giglio et al. (2023).

5.1.4 Species Awareness

With these empirical main findings to reveal the relationship between biodiversity exposure and municipal financing, we also account for the heterogeneous effects of either issuer or lender over the municipal finance structurally. In the Pástor et al. (2021) and Pedersen et al. (2021), they document that investors with green awareness tends to require for lower risk premium tend to require for a lower premium due to non-pecuniary external effect. This experiment is more sensible within the municipal bond market, since the municipal bond market has market segmentation for taxation issue as Babina et al. (2021b) shows. This contributes to a local bias for the regional investors. Given these settings, we test these heterogeneity by measuring local species protection awareness. We use the environmental petition as proxy for the local species protection awareness for investors. Finally, we test

this implication within municipal bond market by exploiting the following equation:

$$yield_{i,t} = \beta_0 Biodiversity_{i,t} \times Awareness_{i,t} + \beta_1 Biodiversity_{i,t} + Control_{i,t} + \delta_i + \delta_t + \epsilon_{i,t}$$

Where $Awareness_{i,t}$ refers to the petition for species protection in county i at time t. Our focus is the coefficient of β_0. Table 8 summarizes the main results. Column (1) tracks the intensive margin of financial borrowing cost for municipalities from the interactive term β_0, we find the counties with higher species protection awareness tend to have lower municipal bond yield. One standard-deviation increase in interactive terms contributes to 11.64 bps reduction, which is equivalent to 1.2% decrease in municipal bond yield. This illustrates the consistence with Pástor et al. (2021) and Pedersen et al. (2021) predictions. More importantly, this species protection contributes to not only intensive margin but also extensive margin by with 1.64% (2.89%) change in total bond issuance. Thus, our paper implies that species protection awareness are helpful for reducing the financial cost of borrowing.

5.1.5 Heterogeneous Issuer

Besides investor characteristics, another important issue that drives heterogeneity among the equilibrium is the issuer side heterogeneity. Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2023) show consistent evidence that carbon-intensive firms are exposed more to the carbon transition risk and compensated for a higher return. We consider the issuer types[7] and define the issuers with higher exposure to climate change risk. Then, we incorporate the heterogeneity into the pricing structure and explore its cross-sectional variation:

$$yield_{i,t} = \beta_0 Biodiversity_{i,t} \times Sensitivity_{i,t} + \beta_1 Biodiversity_{i,t} + Control_{i,t} + \delta_i + \delta_t + \epsilon_{i,t}$$

[7]The issuers include: 1) Electric Utilities, encompassing both standalone electric utilities and combined electric and gas utilities; 2) Water Supply and Irrigation Systems, referred to as water utilities, essential for water resource management; 3) Hydroelectric Power Generation, highlighting renewable energy generation through water resources; 4) Alternative Energy Sources, focusing on issuers involved in non-traditional renewable energy projects; 5) Pollution Control, which includes entities dedicated to reducing environmental pollution; 6) Solid Waste and Resource Recovery, dealing with waste management and recycling efforts; 7) Natural Gas Distribution, known as gas utilities, which are crucial in the energy supply chain; 8) Renewable Energy-Related Companies, which specifically focus on the production and innovation in renewable energy technologies; 9) Construction Companies engaged in green building projects, which emphasize sustainable construction practices; and 10) Environmental and Sustainable Development Agencies.

where $Sensitivity_{i,t}$ is defined based on the issuer types, like sensitive industry with higher exposures to climate risk or not. Consistent with Bolton and Kacperczyk (2021),Hsu et al. (2023), for the security issuers with higher climate risk, the security pricing tends to have higher premiums than the others. This pattern still holds in our municipal bond market against the biodiversity exposure. In Table 9, column (3) shows that if the issuer belongs to the sensitive sectors. The premium on biodiversity exposure is higher than non-sensitive sectors. With one standard deviation change in biodiversity exposure, the premium for sensitive sector is 1.24% higher in comparison with the 0.47% from the non-sensitive issuers. The 1.24% (0.47%) is equivalent to 12.58% (4.8%) cross-sectional bond yield yield average. Both estimations are of statistical significant within the full samples. In sum, this experiment convinces the large heterogeneous effect in response to the biodiversity exposure. Among the issuers with higher climate sensitivity, the risk premiums are of greater economic magnitude than the counterparts.

Given the close relationship between municipal bonds and public finance, we also examine the pricing heterogeneity of biodiversity exposure, contingent on the underlying sustainability, since government spending on biodiversity infrastructure is also one of essential parts influencing government sustainability. Table 9 shows the main results based on the sustainability of the municipal bond issuance. Compared with non-GO bond issuance, the GO bonds have much lower biodiversity transition risk premiums. There are both statistical significance for GO bond and non-GO bond; however, for the GO bond, the yield is much smaller (12.6 bps) than the non-GO bond (58.1 bps) with one standard deviation increase in biodiversity transition risk. This effect implies that government sustainability to biodiversity exposure is dependent on underlying funding. The issuance of municipal bond back up with taxation can effectively mitigate financial borrowing cost.

5.1.6 Term Structure

Another essential question is about the term structure of the municipal bond pricing. Painter (2020) documents that the assets with longer maturities are more exposed to the sea-level risk; however, Giglio et al. (2021) shows that the real estate cash flows exposed to flooding risk tend to have a downward slope since the short mature assets are exposed more to the climate risks. However, within the framework of biodiversity exposure, it's ambiguous to verify the exposures of bio-

diversity exposure against the maturities. On the one hand, biodiversity exposure is a forward-looking risk that has not yet fully materialized. With higher public attention, it's convincing to believe that there will be advanced ecosystem amelioration tackling the species issues. On the hand, recent scientific evidence also challenge and pinpoint that there will be tightening critical habitat protection in the near future to restrict human behaviors. To testify this hypothesis, we conduct the following equations to explore investors' risk perception against horizons:

$$yield^{j}_{i,t} = \beta_0 Biodiversity_{i,t} + Control_{i,t} + \delta_i + \delta_t + \epsilon_{i,t}$$

where j denotes the maturities of yield-to-maturity through different horizons. We classify the maturity of debts into 3 categories as "less than 8 years", "longer than 8 years but shorter than 16 years" and "longer than 16 years". The results are displayed in Table 10. As the maturities get longer, the yields tend to be smaller compared with others. For the group with shortest maturity, the yield-to-maturity tends to get 1.21% higher with one standard deviation change in biodiversity. In contrast, the yield-to-maturity for bonds with longer (middle) horizons gets 1.18% (1.14%) higher risk premiums. The economic magnitude for longer (middle, shorter) maturities are 13.6% (13.3%, 12.8%) of full sample average yield-to-maturity. Our experiment verifies the time horizon heterogeneity in response to biodiversity exposure. In general, the assets with longer horizons are considered with less biodiversity exposure exposure as Giglio et al. (2021) shows for property markets.

5.2 Identification

Within the biodiversity exposure framework, we document a positive relationship between bird biodiversity risk and municipal borrowing costs. However, another question arises since it's still ambiguous for us to acknowledge about the exogenous shocks that generate these patterns. Following the framework of climate finance literature, there exist multiple exogenous uncertainties that might drive the performance of the bird biodiversity. One is about the physical risk as emphasized in Bansal et al. (2017). This implies that as ecological biodiversity deteriorates, there will be forward-looking natural disaster. Alternatively, there are also physical capital disasters as in Hong et al. (2023). In our paper, we finally provide empirical evidence from a critical habitat regulation perspective and identify a consistent

pattern that the findings can be explained within the ESA policy framework.

To identify the effect of ESA on both finance and ecological fundamentals, we implement a staggered DiD method to explore the causal effect of critical habitat protection on finance and ecological effects:

$$Y_{i,t} = \beta_0 D_{i,t} + Control_{i,t} + \delta_i + \delta_t + \epsilon_{i,t}$$

where $Y_{i,t}$ denotes our main variables for tests. The key indicator for treatment is $D_{i,t}$ for county i at time t. We define the treated group as the county i at t when it's first required by the federal regulation to protect the endangered species. The rest of the counties who are not exposed to the ESA regulations are defined as control groups. The assumption for identification relies on the exogenous enforceability of the federal critical habitat protection and no other exogenous forces to endogenize the enforcement of the ESA protection. In addition, to address the imbalance issues for staggered DiD as discussed in Baker et al. (2022), we follow the Callaway and Sant'Anna (2021) to conduct a robust DiD inference.

5.2.1 Bond Pricing

Our first assumption for biodiversity exposure still holds in the empirical test for pricing. The difference is that at the identification stage, we hypothesize that the biodiversity is driven by the ESA regulation. Because of the tightened policy on biodiversity, the local economies are restricted experiencing higher growth risk. The regional governments in response to the policy risks cannot hold a sustainable fiscal budget.

To verify this empirical fact, We first employ the bond yield for $Y_{i,t}$ to explore whether critical habitat protection is a driving force for municipal bonds or not. Within DiD causal experiment, Table 11 shows that compared with the control group, the treated group municipal yields increase by 6.72% (6.09%) conditional on how we specify the confounding variables. The positive relationship implies that the stringent critical habitat protection contributes to a higher risk for regional economy. Consistently, we also explore this effect from credit rating agency and document relative evidence that with the enforcement of the ESA regulation the local economic credit ratings decrease by 2.69 (2.48) significantly. Both downgrades have great economic magnitude and are equivalent to 14.8% (13.6%) reduction in average credit ratings.

In appendix, Figure shows a pattern for the parallel trend ex-ante but the treated effect is both statistically significant and of great economic magnitude. The figure displays the impact dynamically. Even after 5 periods of critical habitat protection shocks, the bond yields are still significant. Consistently, we verify the causal effect through rating agencies as well. Figure 8 shows the trend for Moody's credit rating after the ESA shocks. The figure verifies a clear downgrade trend after 5 periods of the initial regulation events. Overall, with these regulation events, we identify the causal links between endangered species protection and municipal bond premium. We confirm that investors perceive these risks through credit rating agencies.

5.2.2 Employment Growth

In light of the higher risk premium associated with holding municipal bonds, we also investigate the impact of the Endangered Species Act (ESA) regulations on regional employment fundamentals. Table 12 presents our findings on employment ratios, demonstrating that ESA regulations constrain local economies and reduce employment opportunities. Consistent with the research of Ferris and Frank (2021a), which showed that regulatory restrictions can hinder economic activity, our results indicate that ESA protections restrict corporate activities, leading to a decline in local employment figures. We specifically analyze micro-level establishment employment and match employment data with biodiversity information to explore the correlation between the NETS employment ratio and the stringency of biodiversity regulations. The results show that under stricter critical habitat protections, county-level employment decreases by an average of 3.42 jobs per firm, accounting for an 8.6% reduction in total employment in the average local firm, even after controlling for confounding variables.

To validate the parallel trend assumption, Figure in Appendix illustrates that following ESA protection events, employment in the treated groups significantly declines. This evidence underscores the negative relationship between economic constraints and ESA regulations, highlighting the potential economic trade-offs of such policies and the importance of careful consideration in their design.

5.2.3 Real Estate Revenue

Besides employment through the corporate, an alternative channel for government debt sustainability is the income from real estate. Goldsmith-Pinkham et al. (2023b) documents that sea-level contributes to higher risk premium compensation through the property channel since the underlying real estate values might be threatened by the physical sea-level risk. We further check this economic channel by switching with property price in the staggered DiD. Table 13 identifies the causal link between housing valuation and species protection. There exists statistically significant negative relationship between housing valuation and ESA regulation. The reduction ranges from 10,616 to 28,238 dollars conditional on the housing types. Compared with market averages, these reductions are equivalent to around 6%(Condo & Single Family), 5.32%(Single Family) and 15.24%(Condo) respectively. Finally, in order to verify the parallel trend assumption, we also plot the in the Appendix. For the robust concern, we show the figures for single family house and condo with parallel trends in Appendix. The price change is consistent with the previous documented story in climate finance literature; however, it holds similarly with regard to real estate market. Due to the ESA implementation of the vacant land value, the market value of the land or property price might be reduced as Auffhammer et al. (2020) shows. The potential link is not only because of the restriction over land usage but also because of forward looking constraints on property land usage.

5.2.4 Ecological Biodiversity

Finally, we identify whether ESA regulation is one of the exogenous forces driving bird biodiversity. This assumption is built upon the classic argument on enforceability and biodiversity protection. Accounting for the enforceability of ESA, we implement a forward-looking bird biodiversity to capture the materialization of the species regulation. Therefore, our underlying assumption is that the Endangered Species Act (ESA) effectively protects regional species from extinction.The relevant bird biodiversity can be ameliorated. As show in Table 14, after the regulatory shocks, treated counties have significantly higher bird biodiversity during the post-event. This effect is of greater economic magnitude since the 15% increase is equivalent to a large proportion of the bird biodiversity average. We also have

verification regarding the parallel trend assumption for bird biodiversity. There is an upward trend for the average treated estimation and the trend is statistically significant during the periods of post events. This highlights our underlying assumption that the exogenous shocks from regulatory policy dive the post-event performance, but during the ex-ante period, there is no clear divergence. In sum, we implement a staggered DiD structure to identify the exogenous force driving our biodiversity exposure from ESA regulation. Combining with previous evidence, we show that our findings on the relationship between bird biodiversity and municipal bond-related performance are due to the causal connection between bird biodiversity and regulatory risk.

6 Conclusion

We propose a novel bird biodiversity measure to assess the evolution of county-level biodiversity. Unlike classical measures, such as those documented in Giglio et al. (2023), our approach addresses potential endogeneity arising from self-reported data sources. Moreover, our measure is designed to flexibly capture the time-varying effects of bird biodiversity. Utilizing this biodiversity index as a proxy, we investigate the critical question of whether a significant relationship exists between biodiversity exposure and municipal finance.

Our findings reveal a compensatory relationship between bird biodiversity and municipal bond pricing. At the county level, municipalities facing heightened biodiversity exposure incur higher borrowing costs. Specifically, a one-standard-deviation increase in biodiversity exposure is associated with a 42.4 (63.3) basis point (bps) rise in municipal bond yields, conditional on ecological and economic controls, while the extensive margin of financial activities contracts by 0.61%. This pricing heterogeneity underscores the role of regional species protection awareness, which appears to mitigate financial friction. Furthermore, we identify that this economic mechanism is driven by the interaction of ecological and financial information, as evidenced by enriched biodiversity and lower credit ratings. By leveraging the federal Endangered Species Act (ESA) as an exogenous shock, we causally demonstrate that stringent species protection policies are the driving force behind the observed pricing pattern.

Our empirical framework lays the groundwork for future research in the bur-

geoning field of biodiversity finance. Theoretically, our findings suggest that policymakers seeking to attract capital for biodiversity projects can potentially reduce financial borrowing costs through market mechanisms. Additionally, from the perspective of municipal bond pricing literature, our work incorporates natural resources as a factor in pricing and elucidates the economic channels through which species protection regulations can take effect. These risk propagation channels offer valuable insights for policymakers aiming to devise more effective strategies for global environmental protection.

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7 Figures

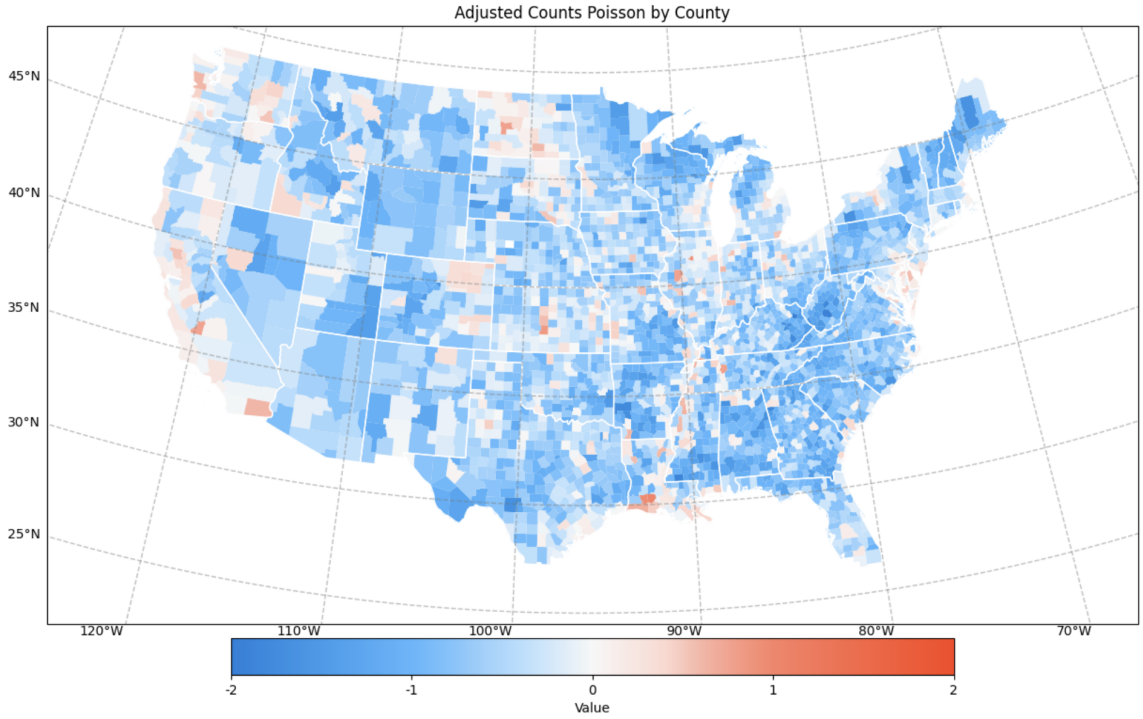


Figure 1: Heatmap of Biodiversity at the County Level Cross Section

Note: This figure displays the geographic distribution of adjusted bird biodiversity across U.S. counties, calculated using data from the eBird dataset, a global citizen science initiative managed by the Cornell Lab of Ornithology. The data have been organized into a county-year-month panel format for analysis. The final dataset covers 3,094 counties, with each county's value representing the average bird biodiversity for each month from 2002 to 2022. The white lines on the map indicate state boundaries, providing a clearer view of bird biodiversity distribution within states.

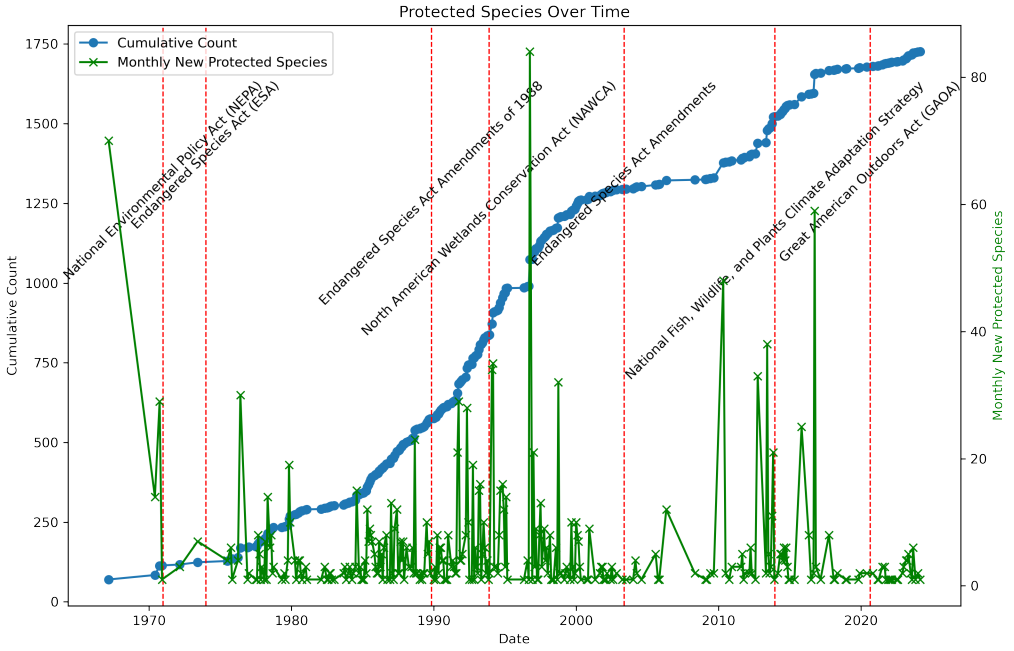


Figure 2: Protected Species Over Time

Note: This figure depicts the changes in the number of species protected at the federal level under the Endangered Species Act (ESA) in the United States from 1970 to 2022, based on data obtained from the official ESA website. The dataset includes the specific dates when each species was added to the protection list. To smooth the data fluctuations, the information has been aggregated to a monthly level. The blue line represents the cumulative number of species added to the protection list, while the green line shows the number of new species added each month.Additionally, the figure marks several significant environmental legislative events in U.S. history with red lines, including the 1970 National Environmental Policy Act (NEPA), the first comprehensive environmental protection law in the U.S.; the 1973 Endangered Species Act (ESA), which provided a critical legal framework for protecting endangered species; major ESA amendments in 1982 and 1988; the 1993 North American Wetlands Conservation Act (NAWCA), aimed at protecting endangered species' habitats; the 2003 ESA enhancements; the 2013 Climate Adaptation Strategy; and the 2020 Great American Outdoors Act (GAOA), which provided long-term funding for national parks, public lands, and species protection.The left Y-axis indicates the cumulative number of protected species, while the right Y-axis shows the monthly number of newly protected species.

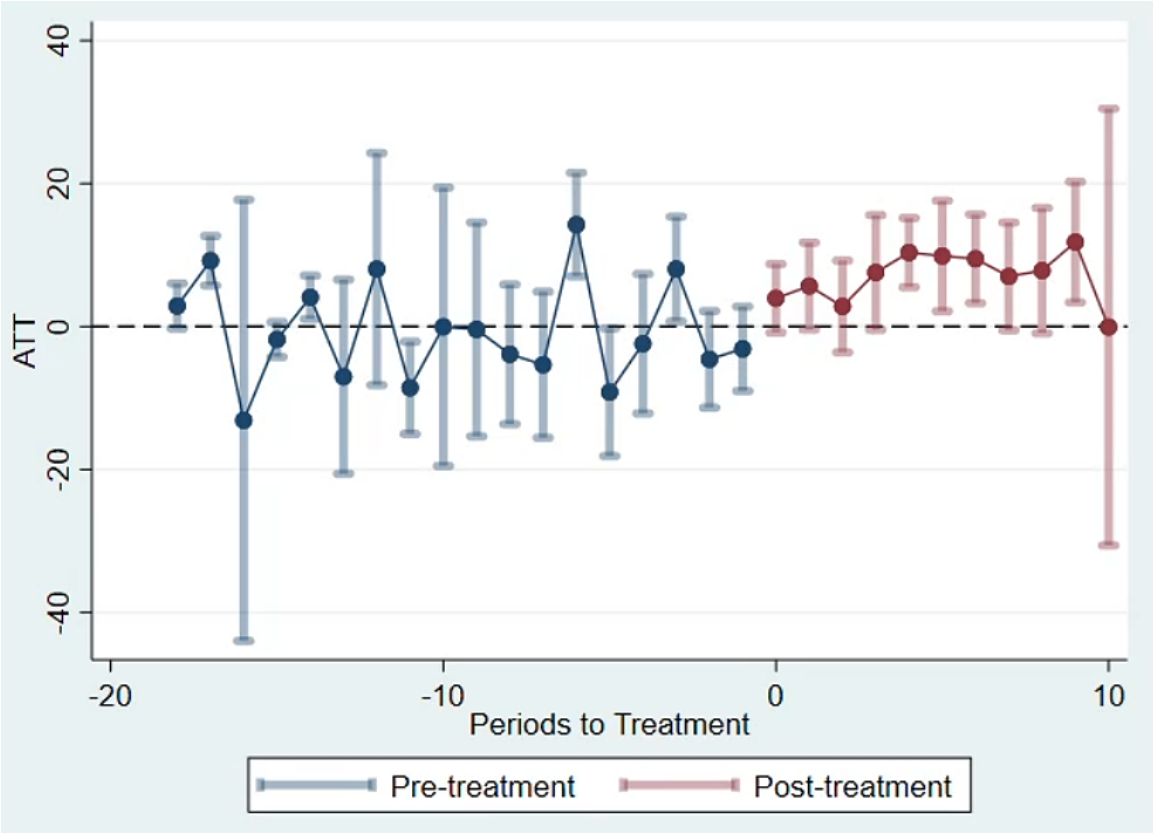


Figure 3: Parallel Trend on Municipal Bond Yields

Note: This figure plots the treatment effect of newly added ESA-protected species on the average annual yield of municipal bonds at the county level, using the stacked DiD (difference-in-differences) specification based on Callaway (2021). The outcome variable is the county's average annual yield to maturity, derived from the SDC database. This yield is calculated by equating the bond-year's transaction volume-weighted average price to the present value of its promised cash flows. The figure presents the average yield to maturity for each county by year, with data constructed at the county-year level, spanning from 2002 to 2022. To control for other factors that might influence bond yields, control variables include water area, land area, total employment, GDP, and personal income, all measured at the county-year level. Water and land area data come from the census, while data on total employment, GDP in current dollars, and average personal income per county-year are sourced from the Bureau of Economic Analysis (BEA). The shock years refer to the years when bird, fish, and invertebrate species were newly added to ESA protection, with data directly obtained from the ESA website. The figure shows the trends for each county before and after treatment, with the blue line representing pre-treatment trends and the red line indicating post-treatment trends. Vertical bars depict 95% confidence intervals, with standard errors clustered at the state level.

8 Table

Table 1: Determination of County-Level Biodiversity

	Dependant: Biodiversity	
	model1	model2
VARIABLES	(1)	(2)
Avg_Flooding_Risk_Rate	0.103	
	(0.65)	
Sum_Flooding_Risk_Rate		-0.0059
		(-0.69)
Water_Area	13.32	13.34
	(0.97)	(1.00)
Land_Area	-9.43	-9.45
	(-1.42)	(-1.42)
Total_Employment	0.39**	0.42**
	(2.21)	(2.34)
GDP	-2.21	-2.07
	(-1.17)	(-1.18)
Personal_Income	0.02	-0.26
	(0.01)	(-0.13)
Constant	-0.44***	-0.42***
	(-16.30)	(-17.45)
Observations	188,760	188,760
R-squared	0.304	0.350
Year FE	YES	YES
City FE	YES	YES
State FE	YES	YES
Cluster	YES	YES

Note:The first panel reports regression results assessing the relationship between biodiversity and various risk factors using two model specifications. Model 1 focuses on the average flooding risk rate (Avg_Flooding_Risk_Rate) within a county as a key independent variable, while Model 2 examines the total flooding risk rate (Sum_Flooding_Risk_Rate). Control variables in both models include Water Area, Land Area, Total Employment, GDP, and Personal Income, providing a comprehensive overview of factors potentially influencing biodiversity. These models control for fixed effects at the county, city, state, and year levels to isolate the effects of flooding risk from other confounding factors. The standard errors are clustered at the state level, and robust t-statistics are reported in parentheses. ***p < 0.01; **p < 0.05; *p < 0.1.

Table 2: Correlation of eBird and Alternative Biodiversity

	Biodiversity	Std_Biodiversity	Emp_Bio	Gdp_Bio	Area_Bio	Species_Bio
Biodiversity	*	*	*	*	*	*
Std_Biodiversity	1.00	*	*	*	*	*
Emp_Bio	-0.05	-0.05	*	*	*	*
Gdp_Bio	-0.10	-0.10	0.71	*	*	*
Area_Bio	0.02	0.02	-0.03	-0.04	*	*
Species_Bio	0.15	0.15	-0.18	-0.25	0.13	*

Note:This table presents the correlation coefficients between different measures of biodiversity. The variables Biodiversity and Std_Biodiversity represent the biodiversity measures used in our current study. In contrast, the variables Emp_Bio, Gdp_Bio, Area_Bio, and Species_Bio are derived from Giglio (2021) and represent alternative biodiversity exposure metrics: Emp_Bio (employment-based biodiversity exposure), Gdp_Bio (GDP-based biodiversity exposure), Area_Bio (area-based biodiversity exposure), and Species_Bio (species-based biodiversity exposure).

Table 3: Summary of Statistics for County and Bond Variable

Variable	Q1 Mean	Q1 Std	Q2 Mean	Q2 Std	Q3 Mean	Q3 Std	Q4 Mean	Q4 Std	ALL Mean	ALL Std
Yield	7.286	22.515	12.960	31.219	13.241	31.412	8.549	24.387	9.871	26.744
MOODY_Rating	18.186	3.922	16.573	4.507	16.394	4.440	19.111	3.490	18.171	4.042
YTM	5.752	10.009	13.318	12.748	12.672	12.765	7.562	11.881	8.977	12.203
Awareness*Biodiversity	-0.033	0.559	-0.014	0.368	-0.002	0.319	0.010	0.312	-0.007	0.388
Awareness	0.027	0.411	0.024	0.370	0.023	0.355	0.021	0.343	0.024	0.372
Biodiversity	-1.068	0.705	-0.669	0.709	-0.354	0.720	0.070	0.762	-0.447	0.835
Prob. Of issuance	0.158	0.365	0.183	0.387	0.251	0.434	0.266	0.442	0.213	0.410
Amount of issuance	164.445	2172.189	100.037	2635.973	148.900	1988.112	244.465	2897.956	163.055	2439.894
Employment (NETS) Ave	42.00	41.06	39.94	37.05	38.43	31.09	38.06	26.84	39.47	33.99
Water Area (10^9)	0.26	1.49	0.27	1.29	0.38	1.70	0.53	1.66	0.35	1.54
Land Area (10^9)	2.53	5.21	2.94	10.00	3.41	15.74	2.40	2.99	2.80	9.780
Total employment (10^3)	21.36	67.61	49.61	122.16	98.52	240.42	146.65	429.31	79.28	260.62
GDP (10^6)	1.70	7.79	4.15	11.88	8.80	25.03	14.40	50.60	7.29	29.56
Personal income (10^6)	1.56	4.87	3.60	9.11	7.64	19.39	11.80	36.43	6.17	21.67
sfr&condo Price (10^6)	0.32	0.39	0.31	0.17	0.33	0.19	0.40	0.32	0.34	0.28
condo Price (10^6)	0.19	0.12	0.16	0.08	0.18	0.10	0.20	0.13	0.19	0.11
Sfr Price (10^6)	0.18	0.20	0.18	0.10	0.20	0.12	0.24	0.18	0.20	0.15
Prob. Of issuance GO bonds	0.007	0.084	0.006	0.075	0.011	0.104	0.014	0.119	0.009	0.096
Amount of issuance GO bonds(10^6)	0.10	0.23	0.18	0.38	0.27	0.62	0.27	0.72	0.13	0.41
Avg Flooding Risk Rate	0.082	0.139	0.078	0.141	0.082	0.131	0.099	0.145	0.085	0.139
Sum Flooding Risk Rate	0.674	1.258	0.870	1.787	1.110	2.059	1.716	4.389	1.083	2.672

Note: This table presents a summary of the variables utilized in the regression analysis of municipal bond impacts, with observations classified into two categories: bond-year-month and county-year-month, spanning the period from 2002 to 2022. **Yield** : Represents the average annual yield to maturity at the county level, calculated from bond-month transaction data. This yield equates the transaction volume-weighted average price with the present value of the bond's promised cash flows. Data sourced from the SDC database. **Years to Maturity (YTM)**: Indicates the number of years from the last transaction date of a bond in a given bond-year-month to its maturity date, derived from the SDC database. **MOODY_RATING**: Moody's rating levels for municipal bonds, where ratings are numerically encoded as follows: from 'C' (1) to 'Aaa' (21), with specific ratings for notations like 'NP' (0) and 'NR' (None). This variable classifies the credit quality of the bonds. **Water_Area and Land_Area**: Represents the water and land areas of counties, respectively, with data obtained from U.S. Census Bureau records, reported on an annual county basis. **Total_employment, GDP, Personal_income**: Local employment rates, GDP, and average personal income per capita, respectively, sourced from the BEA database, presented on a county-year basis. **Awareness**: Based on data from petitions filed under the Endangered Species Act (ESA) to list or delist species, reflecting the number of petitions concerning species within a state for a given month. **Biodiversity**: Adjusted monthly biodiversity index previously referred to in Figure 1 of the analysis. **Employment (NETS) Ave**:The summed total of actual employment values from the NETS database, attributed to each county annually, represents local employment data. **SFR & Condo Price**: Indexes from Zillow reflecting housing prices in counties, reported monthly on a county-year basis. **Prob. of Issuance & Amount of Issuance**: Probability and total volume of municipal bond issuance in a given county and month. **Prob. of Issuance & Amount of Issuance for GO bond**: The probability and total volume of general obligation (GO) bond issuance in a given county and month **Flood Risk Data**: Flood risk data downloaded from Giglio et al. (2021), used as proxies for physical flood or sea-level risks in county-level regions. Variables include Avg_Flooding_Risk_Rate and Sum_Flooding_Risk_Rate, representing the average and total flood risk levels in a county.

Table 4: Municipal Pricing Comparison with Alternative Biodiversity Measure

VARIABLES	Model 1 Moody_rating	Model 2 Yield
Biodiversity	-0.80*	2.09***
	(-1.99)	(2.76)
Emp_Bio	0.08	-1.19**
	(0.41)	(-2.66)
Gdp_Bio	0.42**	-1.59***
	(2.60)	(-3.47)
Area_Bio	-5.25***	2.81
	(-3.92)	(0.38)
Species_Bio	14.8	-15.4
	(1.25)	(-0.86)
Water_Area	-362.25	613.76
	(-0.49)	(0.76)
Land_Area	-16.50	-16.59
	(-0.67)	(-0.89)
Total_Employment	-0.06	11.90***
	(-0.11)	(4.303)
GDP	5.72	-37.22**
	(1.08)	(-2.638)
Personal_Income	-8.43	-102.88***
	(-0.84)	(-3.131)
Constant	11.05***	44.96***
	(9.76)	(6.927)
Observations	61,715	142,421
R-squared	0.46	0.202
State*Month FE	YES	YES
Cluster	YES	YES

Note: This table presents the regression results assessing the impacts on bond yield and Moody's credit rating at the county-year level. This analysis aims to clarify the differences between our Biodiversity index and Giglio's biodiversity exposure measures. The dependent variables are bond yield (Model 2) and Moody's credit rating (Model 1). The principal independent variable is the Biodiversity index, derived from processed eBird data. In addition to the main biodiversity metrics, the models control for Giglio's four biodiversity exposure measures. Additional controls include Water Area (total water area within the county), Land Area (total land area within the county), Total Employment (total number of employed individuals within the county), GDP (gross domestic product of the county), and Personal Income (average personal income per capita within the county). The models include fixed effects for state and month interactions. Standard errors are clustered at the state level. Significance levels are indicated as follows: ***p<0.01, **p<0.05, *p<0.1.

Table 5: Yield and Moody Rating Regressions

	Yield		Moody_Rating	
VARIABLES	model1	model2	model3	model4
Biodiversity	0.51***	0.76***	-0.14*	-0.14**
	(3.17)	(4.06)	(-1.85)	(-2.26)
Water_Area		-75.80		-96.05
		(-0.18)		(-1.54)
Land_Area		662.13***		-97.39***
		(2.61)		(-3.99)
Total_Employment		-18.61**		2.11*
		(-2.35)		(1.94)
GDP		-4.51		1.74
		(-0.28)		(0.47)
Personal_Income		5.13		-20.09***
		(0.27)		(-2.86)
Constant	10.43***	21.52***	17.98***	18.13***
	(279.9)	(5.52)	(1,514)	(42.34)
Observations	276,461	213,405	41,277	48,718
R-squared	0.30	0.30	0.66	0.65
County FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Cluster	YES	YES	YES	YES

Note: This table reports the regression results for bond yield and Moody's credit rating at the county-year level. The sample period covers bond-year-month-level data, with the dependent variables being bond yield (columns 1 and 2) and Moody's credit rating (columns 3 and 4). The main independent variable of interest is the Biodiversity index, derived from the processed eBird data. Control variables include Water Area (the total water area within the county), Land Area (the total land area within the county), Total Employment (the total number of employed individuals within the county), GDP (gross domestic product of the county), and Personal Income (average personal income per capita within the county). These controls account for factors that might influence economic activity and bond market performance. All models include county fixed effects (FE), month fixed effects, city fixed effects, and state fixed effects to control for time-invariant characteristics at these levels. The standard errors are clustered at the state level, and robust t-statistics are reported in parentheses. The table presents results from both models with and without control variables. ***p < 0.01; **p < 0.05; *p < 0.1.

Table 6: Extensive Margin Regression Municipal Bond Issuance over Biodiversity

	model1	model2	model3	model4
VARIABLES	Amount of Issuance	Prob. Of issuance	Amount of GO bond issuance	Prob. Of GO Bond issuance
Biodiversity	-3.24**	-0.0074***	-0.091	-0.00076*
	(-2.50)	(-3.300)	(-1.59)	(-1.74)
Water_Area	-1594.89	-1.83	-72.26**	-0.36
	(-0.47)	(-0.64)	(-2.08)	(-1.47)
Land_Area	305.44	-2.09**	19.18	0.08
	(0.31)	(-2.14)	(1.17)	(0.50)
Total_Employment	-544.74***	-0.30	13.60	0.15
	(-3.16)	(-0.83)	(0.731)	(1.46)
GDP	126.40	3.91**	25.34	0.12
	(0.17)	(2.21)	(0.28)	(0.16)
Personal_Income	2821.38**	-7.74**	96.29	0.94
	(2.30)	(-2.08)	(0.93)	(1.10)
Constant	134.40***	0.32***	-1.63	-0.016
	(8.61)	(13.22)	(-0.72)	(-1.28)
Observations	216,481	216,481	216,481	216,481
R-squared	0.35	0.38	0.22	0.20
County FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Cluster	YES	YES	YES	YES

Note: This table presents the regression results examining the impact of biodiversity on various aspects of bond issuance at the county-year-month level. The dependent variables include the amount of bond issuance (column 1), the probability of bond issuance (column 2), the amount of general obligation (GO) bond issuance (column 3), and the probability of GO bond issuance (column 4). The main independent variable of interest is the Biodiversity index, derived from processed eBird data, which captures the impact of county-level biodiversity on bond market outcomes. Control variables include Water Area (the total water area within the county), Land Area (the total land area within the county), Total Employment (the total number of employed individuals within the county), GDP (gross domestic product of the county), and Personal Income (average personal income per capita within the county). These controls account for factors that might influence economic activity and bond market performance. All models include county, month, city, and state fixed effects to control for time-invariant characteristics at these levels. Standard errors are clustered at the state level, and robust t-statistics are reported in parentheses. ***p < 0.01; **p < 0.05; *p < 0.1.

Table 7: Municipal Pricing Comparison with Alternative Biodiversity Measure

VARIABLES	Model 1 Moody_rating	Model 2 Yield
Biodiversity	-0.80*	2.09***
	(-1.99)	(2.76)
Emp_Bio	0.08	-1.19**
	(0.41)	(-2.66)
Gdp_Bio	0.42**	-1.59***
	(2.60)	(-3.47)
Area_Bio	-5.25***	2.81
	(-3.92)	(0.38)
Species_Bio	14.8	-15.4
	(1.25)	(-0.86)
Water_Area	-362.25	613.76
	(-0.49)	(0.76)
Land_Area	-16.50	-16.59
	(-0.67)	(-0.89)
Total_Employment	-0.06	11.90***
	(-0.11)	(4.303)
GDP	5.72	-37.22**
	(1.08)	(-2.638)
Personal_Income	-8.43	-102.88***
	(-0.84)	(-3.131)
Constant	11.05***	44.96***
	(9.76)	(6.927)
Observations	61,715	142,421
R-squared	0.46	0.202
State*Month FE	YES	YES
Cluster	YES	YES

Note: This table presents the regression results assessing the impacts on bond yield and Moody's credit rating at the county-year level. This analysis aims to clarify the differences between our Biodiversity index and Giglio's biodiversity exposure measures. The dependent variables are bond yield (Model 2) and Moody's credit rating (Model 1). The principal independent variable is the Biodiversity index, derived from processed eBird data. In addition to the main biodiversity metrics, the models control for Giglio's four biodiversity exposure measures. Additional controls include Water Area (total water area within the county), Land Area (total land area within the county), Total Employment (total number of employed individuals within the county), GDP (gross domestic product of the county), and Personal Income (average personal income per capita within the county). The models include fixed effects for state and month interactions. Standard errors are clustered at the state level. Significance levels are indicated as follows: ***p<0.01, **p<0.05, *p<0.1.

Table 8: Interaction Effects of Biodiversity and Local Petition Awareness

	Baseline model	model1	model2
VARIABLES	Yield	Amount of issuance	Prob. Of issuance
Biodiversity*Awareness	-0.30*	2.35**	0.0034*
	(-1.95)	(2.07)	(1.88)
Biodiversity	0.77***	-3.31**	-0.0075***
	(3.30)	(-2.56)	(-3.32)
Water_Area	-77.64	-1593.95	-1.82
	(-0.23)	(-0.47)	(-0.64)
Land_Area	661.97***	306.51	-2.09**
	(3.59)	(0.31)	(-2.14)
Total_Employment	-18.63**	-544.82***	-0.30
	(-2.16)	(-3.16)	(-0.84)
GDP	-4.41	126.15	3.91**
	(-0.27)	(0.16)	(2.21)
Personal_Income	5.07	2821.97**	-7.74**
	(0.27)	(2.30)	(-2.08)
Constant	21.53***	134.36***	0.32***
	(5.89)	(8.61)	(13.23)
Observations	213,405	216,481	216,481
R-squared	0.30	0.35	0.38
County FE	YES	YES	YES
Month FE	YES	YES	YES
City FE	YES	YES	YES
State FE	YES	YES	YES
Cluster	YES	YES	YES

Note:This table presents the regression results examining the interaction effect of biodiversity and environmental awareness on bond market outcomes at the county-year-month level. The dependent variables include bond yield (column 1), the amount of bond issuance (column 2), and the probability of bond issuance (column 3). The main independent variables include the Biodiversity index, derived from processed eBird data, and an interaction term Biodiversity*Awareness, which is calculated as the product of the number of petitions submitted in the given month concerning species in the relevant state and the processed biodiversity index for that month. Control variables include Water Area (the total water area within the county), Land Area (the total land area within the county), Total Employment (the total number of employed individuals within the county), GDP (gross domestic product of the county), and Personal Income (average personal income per capita within the county). These controls are included to account for factors that might influence economic activity and bond market performance. All models include county, month, city, and state fixed effects to control for time-invariant characteristics at these levels. Standard errors are clustered at the state level, and robust t-statistics are reported in parentheses. ***p < 0.01; **p < 0.05; *p < 0.1.

Table 9: heterogeneous bond return of issuer

	GO Bonds	Non GO Bonds	Sensitive Bonds	Non Sensitive Bonds
VARIABLES	Yield	Yield	Yield	Yield
Biodiversity	0.15*	0.70***	1.50**	0.57***
	(1.96)	(4.52)	(2.26)	(3.02)
Water_Area	4422.86***	-118.07	-826.67	-42.08
	(4.31)	(-0.28)	(-0.96)	(-0.13)
Land_Area	4108.55***	649.04***	533.23	626.78***
	(4.41)	(2.61)	(0.64)	(3.61)
Total_Employment	-7.22*	-19.90**	-7.69	-17.58*
	(-1.79)	(-2.20)	(-0.80)	(-1.92)
GDP	26.51	-4.11	41.76*	-8.58
	(1.53)	(-0.24)	(1.76)	(-0.52)
Personal_Income	-23.18	6.01	-109.97**	11.95
	(-1.62)	(0.31)	(-2.37)	(0.638)
Constant	-5.78**	23.58***	28.08***	19.80***
	(-2.61)	(5.28)	(7.43)	(5.27)
Observations	25,305	187,810	12,762	199,460
R-squared	0.40	0.29	0.45	0.31
County FE	YES	YES	YES	YES
Month FE	YES	YES	YES	YES
City FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Cluster	YES	YES	YES	YES

Note: This table presents the regression results examining the impact of biodiversity on bond yield, comparing different bond types. The dependent variable in each column is the bond yield, with the sample split into four groups: (1) GO Bonds (General Obligation Bonds), (2) Non-GO Bonds, (3) Sensitive Bonds, and (4) Non-Sensitive Bonds. The main independent variable of interest is the Biodiversity index, derived from processed eBird data, which captures the impact of county-level biodiversity on bond market outcomes. Control variables include Water Area (the total water area within the county), Land Area (the total land area within the county), Total Employment (the total number of employed individuals within the county), GDP (gross domestic product of the county), and Personal Income (average personal income per capita within the county). These controls account for factors that might influence economic activity and bond market performance. Both models include county, month, city, and state fixed effects to control for time-invariant characteristics at these levels. Standard errors are clustered at the state level, and robust t-statistics are reported in parentheses. ***p < 0.01; **p < 0.05; *p < 0.1.

Table 10: Regression Results

	YTM ≤ 8	$8 <$ YTM ≤ 16	YTM > 16
VARIABLES	Yield	Yield	Yield
Biodiversity	1.45***	1.43**	1.37**
	(4.48)	(2.39)	(2.66)
Water_Area	-1948.52	-2008.18	1307.59
	(-1.10)	(-1.5)	(1.29)
Land_Area	-530.56	197.57	2129.00*
	(-0.30)	(0.17)	(1.90)
Total_Employment	-17.19	-31.37*	-26.06
	(-1.18)	(-1.69)	(-1.11)
GDP	13.66	-21.35	-64.86
	(0.25)	(-0.42)	(-1.00)
Personal_Income	15.77	106.85	154.36
	(0.24)	(0.73)	(1.12)
Constant	17.70**	43.51***	47.24***
	(2.61)	(5.78)	(3.49)
Observations	59,672	21,233	29,900
R-squared	0.35	0.33	0.26
County FE	YES	YES	YES
Month FE	YES	YES	YES
City FE	YES	YES	YES
State FE	YES	YES	YES
Cluster	YES	YES	YES

Note:This table presents the regression results examining the impact of biodiversity on bond yield across different segments of the term structure, as measured by years to maturity (YTM). The dependent variable in each column is the bond yield, with the sample divided into three groups based on the YTM: YTM 8 years (column 1), 8 < YTM 16 years (column 2), and YTM > 16 years (column 3). The main independent variable of interest is the Biodiversity index, derived from processed eBird data, which captures the impact of county-level biodiversity on bond market outcomes. Control variables include Water Area (the total water area within the county), Land Area (the total land area within the county), Total Employment (the total number of employed individuals within the county), GDP (gross domestic product of the county), and Personal Income (average personal income per capita within the county). These controls account for factors that might influence economic activity and bond market performance. The models also include county, month, city, and state fixed effects to control for time-invariant characteristics at these levels. Standard errors are clustered at the state level, and robust t-statistics are reported in parentheses. ***p < 0.01; **p < 0.05; *p < 0.1.

Table 11: Staggered DID Results for Biodiversity Policies

	Yield		Moody's Ratings	
VARIABLES	(1)	(2)	(3)	(4)
ATT	6.72***	6.09**	-2.69**	-2.48*
	(2.77)	(2.34)	(-2.00)	(-1.75)
N	17,432	17,432	3,850	3,850
Controls	YES	NO	YES	NO
Clustered	YES	YES	YES	YES

Note:This table reports the treatment effects of newly added ESA-protected species on municipal bond yields and Moody's ratings using a staggered difference-in-differences (DiD) methodology as outlined by Callaway (2021). Data for this analysis is constructed at the county-year level, spanning from 2002 to 2022.Columns (1) and (2) under "Municipal Bond Yields" quantify the average annual yield to maturity (in basis points) for municipal bonds, derived from the SDC database. These yields calculate the transaction volume-weighted average price against the present value of the bond's promised cash flows. Columns (3) and (4) under "Moody's Ratings" display the treatment effects on municipal bond ratings, converted into a numerical scale ('C'=1 to 'Aaa'=21) sourced from the MOODY database.Control variables, included in one version of each regression and excluded in another, comprise water area, land area, total employment, GDP, and personal income per county-year. These variables are sourced from the U.S. Census Bureau and the Bureau of Economic Analysis (BEA).The shock years used in this analysis correspond to years when bird, fish, and invertebrate species were newly added to ESA protection, with data sourced directly from the ESA website. Standard errors are clustered at the state level to adjust for intra-state correlation, enhancing the robustness of the estimates.Standard errors are clustered at the state level, and robust t-statistics are reported in parentheses. ***p < 0.01; **p < 0.05; *p < 0.1.

Table 12: Staggered DID Results for Biodiversity Policies on Employment

	$Employment\ (NETS)^{Ave}$	$Employment(NETS)^{Ave}$
VARIABLES	(1)	(2)
ATT	-3.40**	-2.60*
	(-2.31)	(-1.78)
N	20,213	21,787
Controls	YES	NO
Clustered	YES	YES

Note:This table presents the results of the parallel trends test using the staggered difference-in-differences (DID) method based on Callaway (2021), with data organized at the county-year level. The employment data are sourced from the NETS database and aggregated to the county-year level. These figures are combined with annual county-level population data from the Bureau of Economic Analysis (BEA) to calculate the average employment rate for each county. The table reports the average treatment effect on the treated (ATT) of newly added ESA-protected species on county employment, with standard errors clustered at the state level. Control variables include water area, land area, total employment, GDP, and personal income, which are included to account for other factors that might influence employment rates. The shock years refer to the years when bird, fish, and invertebrate species were newly added to ESA protection, with data directly sourced from the ESA website. Water and land area data are derived from the census, while data on total employment, GDP in current dollars, and average personal income per county-year are obtained from BEA. Two versions of the model were estimated: one with control variables and one without.Robust t-statistics are reported in parentheses. ***p < 0.01; **p < 0.05; *p < 0.1.

Table 13: Staggered DID Results for Biodiversity Policies on Housing Prices (3 Period Lead)

	Total Housing Prices		SFR Housing Prices		Condo Housing Prices	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
ATT	-20,374.88**	-20,122.48**	-10,772.85*	-10,616.04**	-28,238.51***	-24,009.31***
	(-2.34)	(-2.39)	(-1.80)	(-2.12)	(-3.97)	(-3.11)
N	13,634	13,634	13,569	13,569	7,273	7,273
Controls	YES	NO	YES	NO	YES	NO
Clustered	YES	YES	YES	YES	YES	YES

Note:This table presents the results of the parallel trends test using the staggered difference-in-differences (DiD) method as outlined by Callaway (2021), with data structured at the county-year level. The analysis examines the impact of newly added ESA-protected species on the annual average house price index across counties, using housing data from Zillow. The average treatment effect on the treated (ATT) of ESA listings on different housing price segments for each county is analyzed, focusing on total housing, single-family residence (SFR) housing, and condominiums.Columns (1) and (2) report ATT for the total housing price index, with Column (1) including control variables and Column (2) without controls.Columns (3) and (4) focus on SFR housing prices, similarly presenting results with controls in Column (3) and without in Column (4).Columns (5) and (6) detail the impacts on condominium prices, with controls included in Column (5) and excluded in Column (6).Each model's specification clearly states whether control variables—such as water area, land area, total employment, GDP, and personal income—are included. These controls are sourced from the U.S. Census and the Bureau of Economic Analysis (BEA) and are aimed at accounting for other factors that might influence housing prices. Data on shock years, which mark when species were added to ESA protection, are sourced directly from the ESA website.Data are clustered by state to address potential correlations within states, enhancing the robustness of the estimates. Standard errors are clustered at the state level, and t-statistics are reported in parentheses. ***p < 0.01; **p < 0.05; *p < 0.1.

Table 14: Staggered DID Results for Biodiversity Policies on Biodiversity (3 Period Lag)

	Biodiversity_Lead3	Biodiversity_Lead3
VARIABLES	(1)	(2)
ATT	0.15**	0.15**
	(1.97)	(2.23)
N	14,567	14,567
Controls	YES	NO
Clustered	YES	YES

Note:This table showcases the results of a parallel trends test utilizing the staggered difference-in-differences (DiD) approach, as specified by Callaway (2021). The analysis leverages the Ebird index from Figure 1 to compile an annual average bird biodiversity index for each county. This index measures the impact of biodiversity changes, incorporating a three-year lag to capture long-term effects. The dependent variable examines the trends in bird biodiversity in counties after the inclusion of new species under ESA protection.Data are structured at the county-year level and are clustered by state to address within-state correlations. The control variables—water area, land area, total employment, GDP, and personal income—are included to mitigate confounding factors that might affect employment rates. These controls are sourced from the Census for water and land areas, and from the Bureau of Economic Analysis (BEA) for employment and economic data.The "shock years" are defined as periods when bird, fish, and invertebrate species were added to the ESA's protection list, with data directly obtained from the ESA website. The table displays outcomes from two model specifications: one with control variables and another without. Standard errors are clustered at the state level to ensure robustness, and t-statistics are provided in parentheses. Significance levels are indicated as follows: *p < 0.1; **p < 0.05; ***p < 0.01.

9 Figures

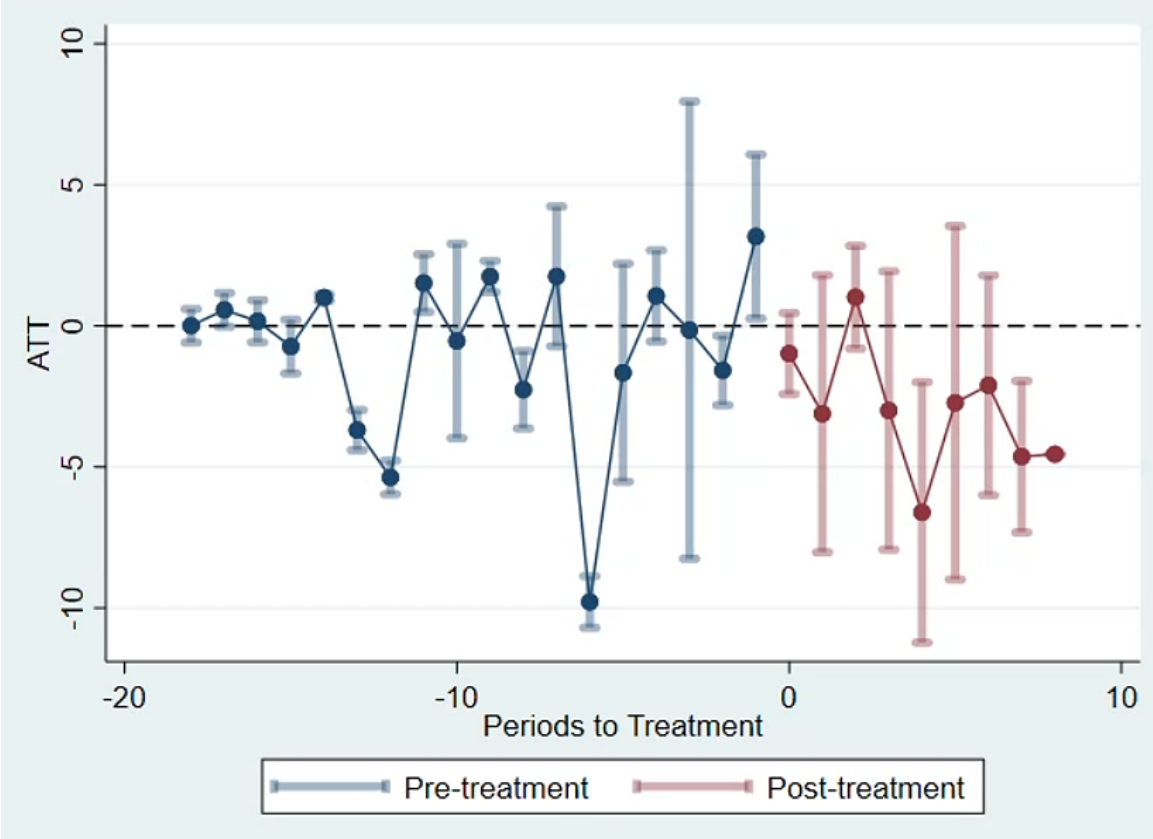


Figure 4: Parallel Trend on Credit Ratings

Note: This figure plots the results of a parallel trends test using the staggered difference-in-differences (DiD) method outlined in Callaway (2021), with data structured at the county-year level. Municipal bond rating data are sourced from the MOODY database and have been mapped to numeric values for analysis, with ratings such as 'C' mapped to 1 and 'Aaa' mapped to 21, thereby converting the ratings into a quantifiable scale. The figure shows the average treatment effect on the treated (ATT) of newly added ESA-protected species on the average annual municipal bond ratings (Y-axis) for each county, with the data clustered by state. Control variables include water area, land area, total employment, GDP, and personal income, all of which are used to account for other factors that might influence bond ratings. The shock years refer to the years when bird, fish, and invertebrate species were newly added to ESA protection, with data directly obtained from the ESA website. The confidence interval is 95%, with standard errors clustered at the state level.

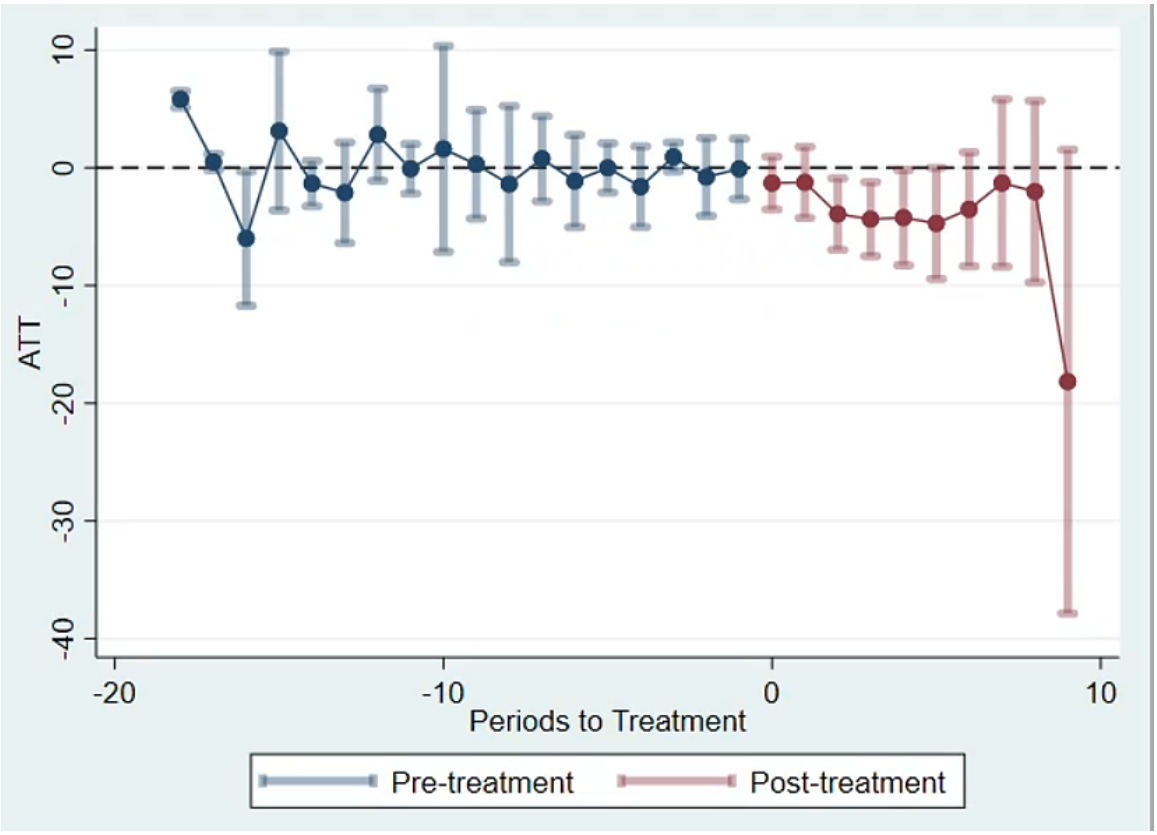


Figure 5: Parallel Trend on Employment

Note: This figure plots the parallel trends test using the staggered difference-in-differences (DID) method based on Callaway (2021), with data organized at the county-year level. The data are sourced from the NETS database, where real employment figures are aggregated to the county-year level. Additionally, these figures are combined with annual county-level population data from the Bureau of Economic Analysis (BEA) to calculate the average employment rate for each county. The figure shows the trend in the annual average employment index across counties, illustrating the average treatment effect on the treated (ATT) of newly added ESA-protected species on county employment. Control variables include water area, land area, total employment, GDP, and personal income, all aimed at controlling for other factors that might influence employment rates. The shock years refer to the years when bird, fish, and invertebrate species were newly added to ESA protection, with data directly sourced from the ESA website. Water and land area data are derived from the census, while data on total employment, GDP in current dollars, and average personal income per county-year are obtained from BEA. The figure shows the trends for each county before and after treatment, with the blue line representing pre-treatment trends and the red line indicating post-treatment trends. Vertical bars depict 95% confidence intervals, with standard errors clustered at the state level.

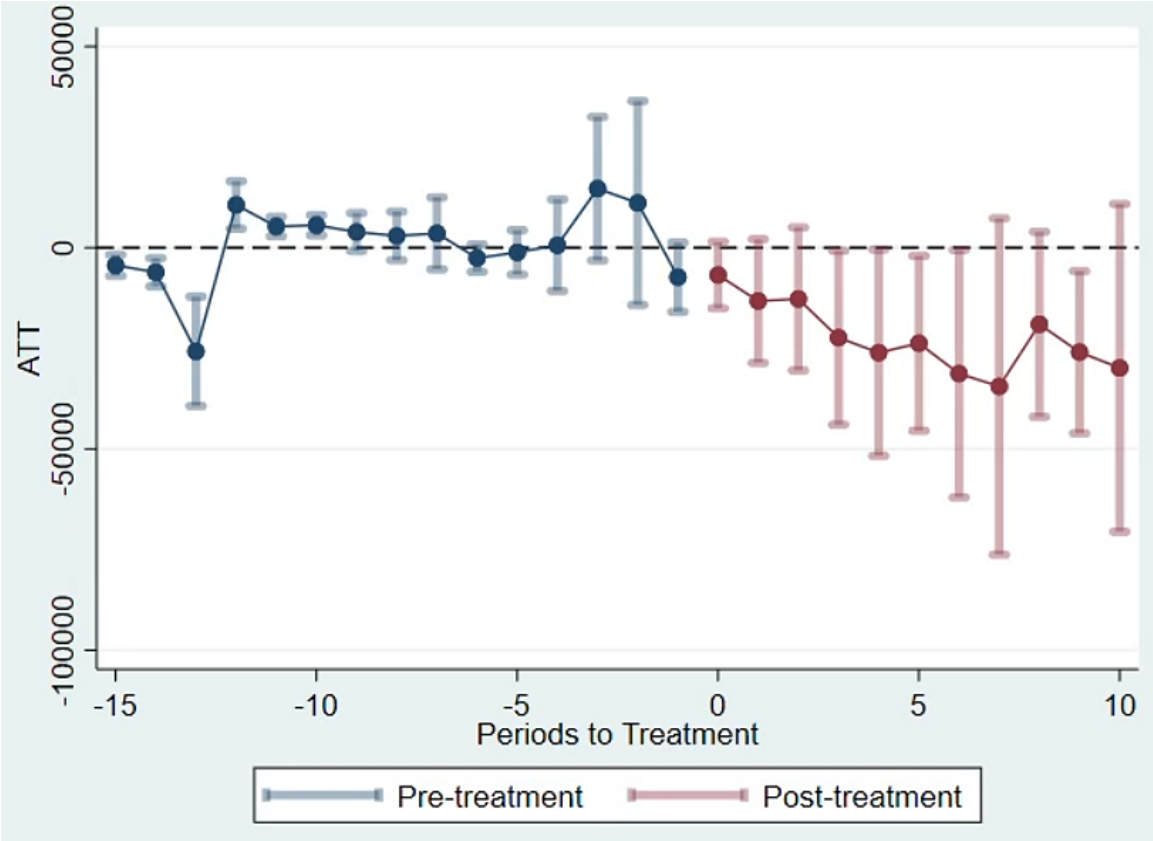


Figure 6: Parallel Trend on Real Estate Price (Single-Family Residences and Condominiums)

Note: This figure plots the parallel trends test using the staggered difference-in-differences (DiD) method based on Callaway (2021), with data organized at the county-year level. The house price index data, sourced from Zillow, reflects the annual average index of home prices, including both single-family homes and apartments. The figure examines the impact of newly added ESA-protected species (lagged by three periods) on the annual average house price index across counties. The y-axis represents the average treatment effect on the treated (ATT) of the ESA listings on the house price index for each county. The data are clustered by state to account for potential correlations within states, and the figure is designed to show how the addition of ESA-protected species influences the trends in house prices across different counties over time. Control variables include water area, land area, total employment, GDP, and personal income, all aimed at controlling for other factors that might influence employment rates. The shock years refer to the years when bird, fish, and invertebrate species were newly added to ESA protection, with data directly sourced from the ESA website. Water and land area data are derived from the census, while data on total employment, GDP in current dollars, and average personal income per county-year are obtained from BEA. The figure shows the trends for each county before and after treatment, with the blue line representing pre-treatment trends and the red line indicating post-treatment trends. Vertical bars depict 95% confidence intervals, with standard errors clustered at the state level.

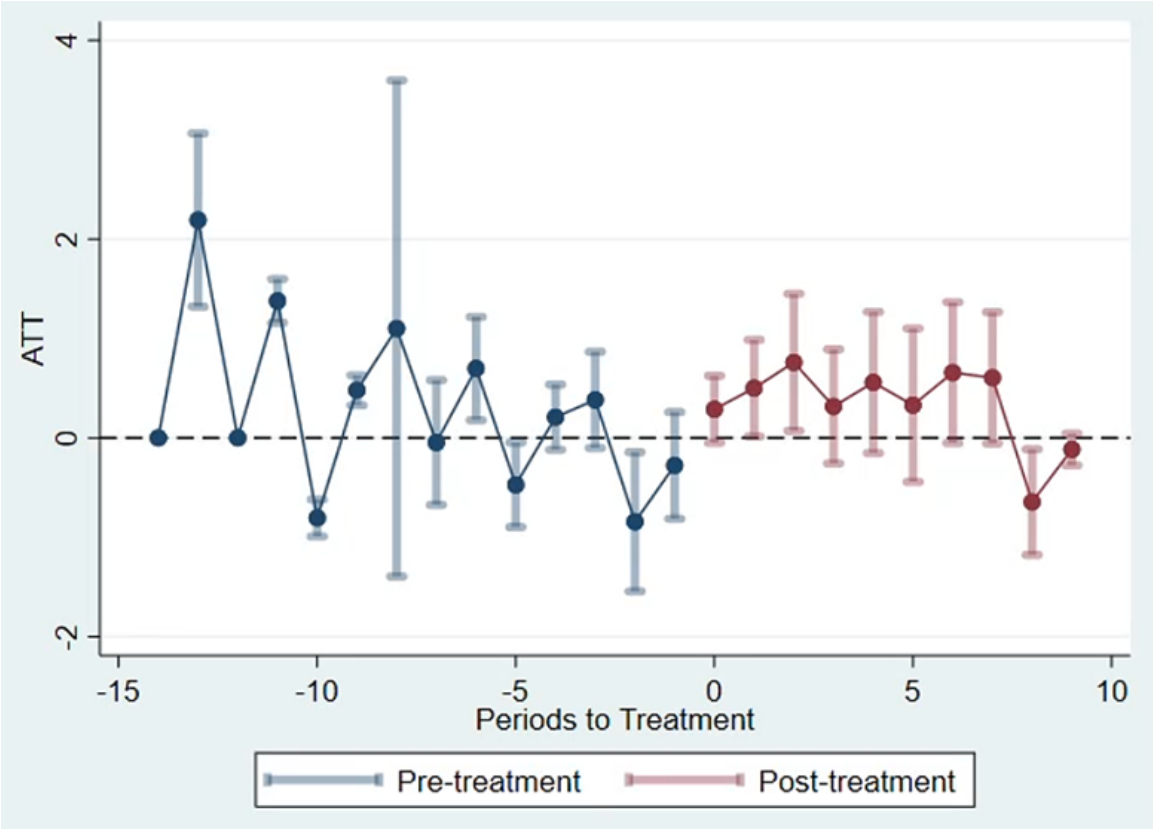


Figure 7: Parallel Trend on Bird Biodiversity

Note: This figure presents a parallel trends test based on the staggered difference-in-differences (DID) method as outlined by Callaway (2021). The data are organized at the county-year level. The figure is derived from our analysis of the processed bird biodiversity index, which utilizes the staggered DID approach, with data units corresponding to county-year observations. The analysis is based on a custom-constructed annual average bird biodiversity index that accounts for the impact of biodiversity within each county and includes a three-year lag to observe long-term effects. The figure illustrates the trend in bird biodiversity across counties following the addition of new species to the ESA protection list. The data are also clustered at the state level to account for within-state correlations. Control variables include water area, land area, total employment, GDP, and personal income, all aimed at controlling for other factors that might influence bird biodiversity. The shock years refer to the years when bird, fish, and invertebrate species were newly added to ESA protection, with data directly sourced from the ESA website. Water and land area data are derived from the census, while data on total employment, GDP in current dollars, and average personal income per county-year are obtained from BEA. The figure shows the trends for each county before and after treatment, with the blue line representing pre-treatment trends and the red line indicating post-treatment trends. Vertical bars depict 95% confidence intervals, with standard errors clustered at the state level.

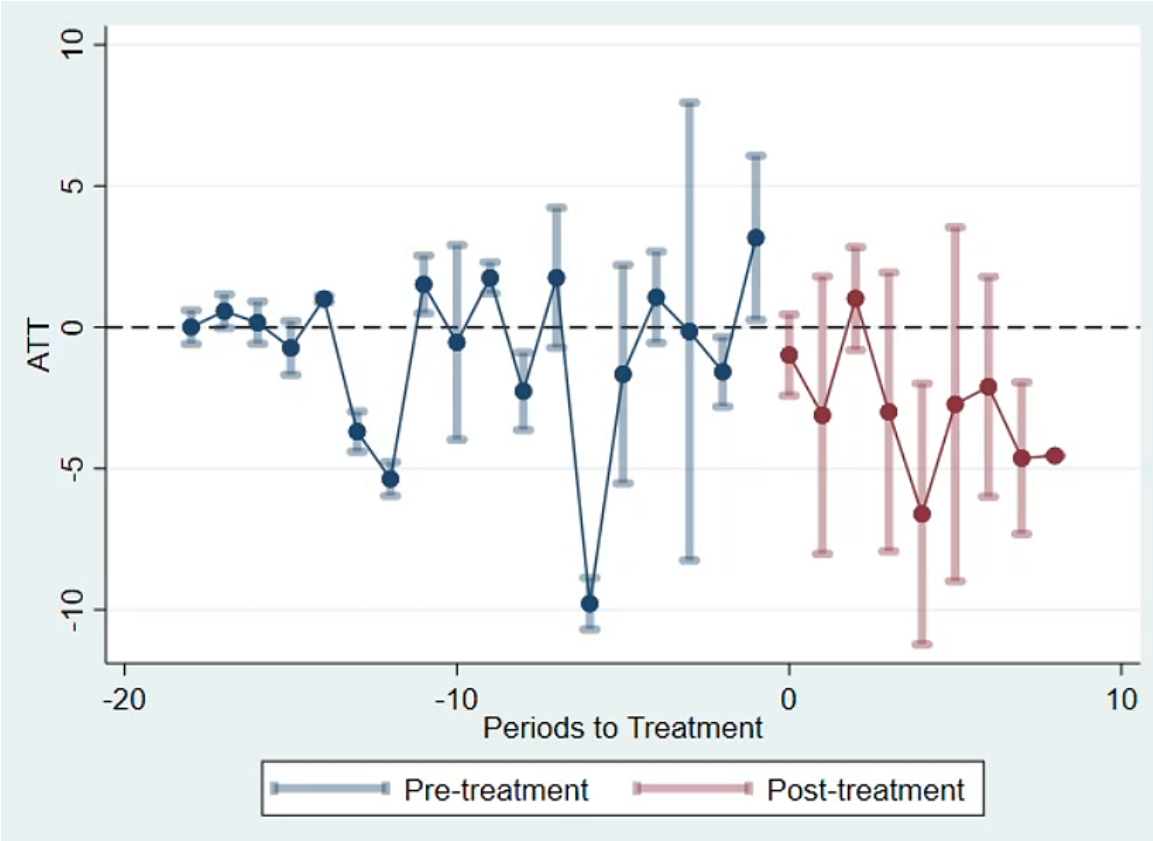


Figure 8: Parallel Trend on Credit Ratings

Note: This figure plots the results of a parallel trends test using the staggered difference-in-differences (DiD) method outlined in Callaway (2021), with data structured at the county-year level. Municipal bond rating data are sourced from the MOODY database and have been mapped to numeric values for analysis, with ratings such as 'C' mapped to 1 and 'Aaa' mapped to 21, thereby converting the ratings into a quantifiable scale. The figure shows the average treatment effect on the treated (ATT) of newly added ESA-protected species on the average annual municipal bond ratings (Y-axis) for each county, with the data clustered by state. Control variables include water area, land area, total employment, GDP, and personal income, all of which are used to account for other factors that might influence bond ratings. The shock years refer to the years when bird, fish, and invertebrate species were newly added to ESA protection, with data directly obtained from the ESA website. The confidence interval is 95%, with standard errors clustered at the state level.

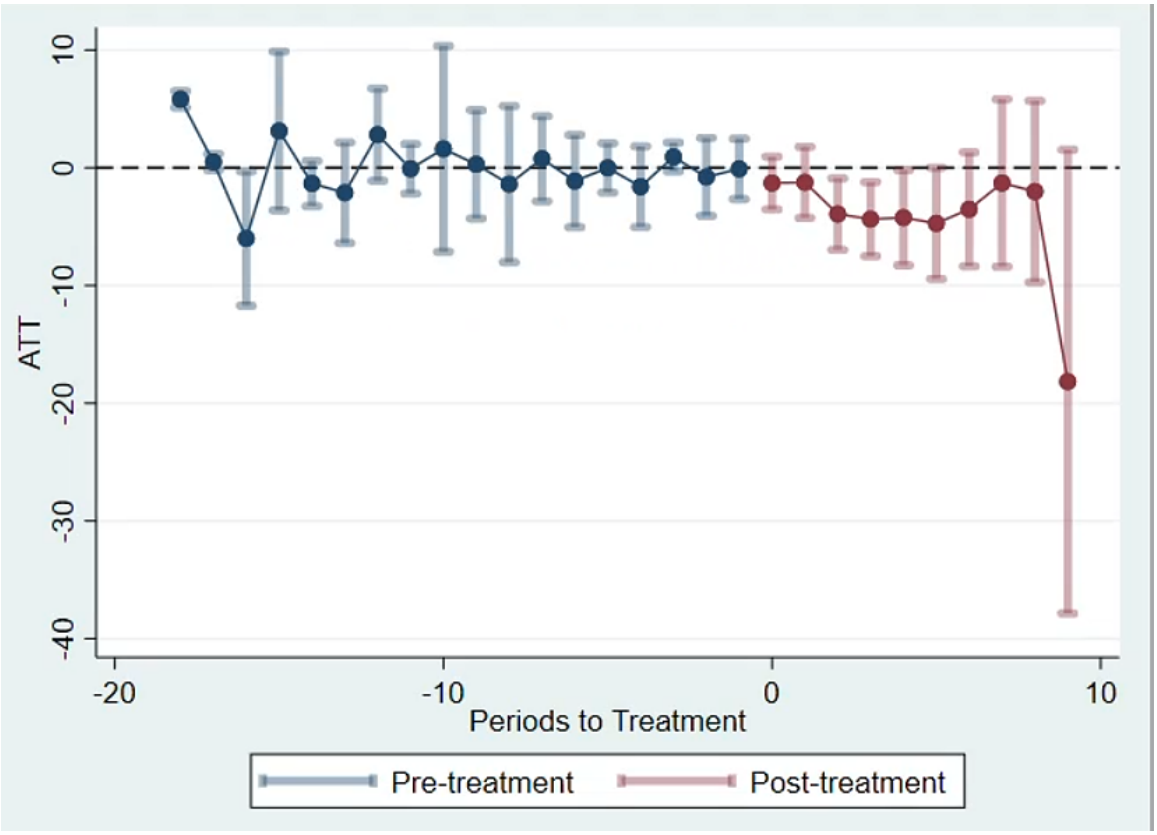


Figure 9: Parallel Trend on Employment

Note: This figure plots the parallel trends test using the staggered difference-in-differences (DID) method based on Callaway (2021), with data organized at the county-year level. The data are sourced from the NETS database, where real employment figures are aggregated to the county-year level. Additionally, these figures are combined with annual county-level population data from the Bureau of Economic Analysis (BEA) to calculate the average employment rate for each county. The figure shows the trend in the annual average employment index across counties, illustrating the average treatment effect on the treated (ATT) of newly added ESA-protected species on county employment. Control variables include water area, land area, total employment, GDP, and personal income, all aimed at controlling for other factors that might influence employment rates. The shock years refer to the years when bird, fish, and invertebrate species were newly added to ESA protection, with data directly sourced from the ESA website. Water and land area data are derived from the census, while data on total employment, GDP in current dollars, and average personal income per county-year are obtained from BEA. The figure shows the trends for each county before and after treatment, with the blue line representing pre-treatment trends and the red line indicating post-treatment trends. Vertical bars depict 95% confidence intervals, with standard errors clustered at the state level.

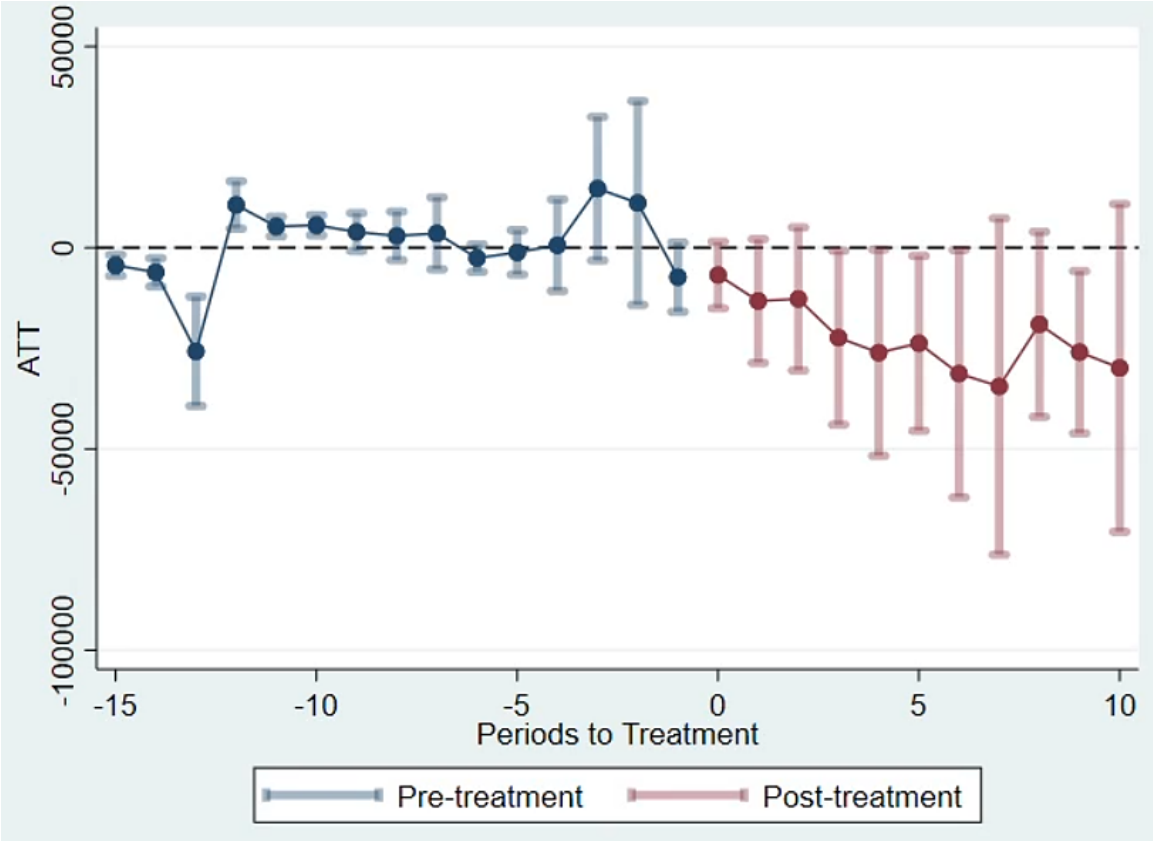


Figure 10: Parallel Trend on Real Estate Price (Single-Family Residences and Condominiums)

Note: This figure plots the parallel trends test using the staggered difference-in-differences (DiD) method based on Callaway (2021), with data organized at the county-year level. The house price index data, sourced from Zillow, reflects the annual average index of home prices, including both single-family homes and apartments. The figure examines the impact of newly added ESA-protected species (lagged by three periods) on the annual average house price index across counties. The y-axis represents the average treatment effect on the treated (ATT) of the ESA listings on the house price index for each county. The data are clustered by state to account for potential correlations within states, and the figure is designed to show how the addition of ESA-protected species influences the trends in house prices across different counties over time. Control variables include water area, land area, total employment, GDP, and personal income, all aimed at controlling for other factors that might influence employment rates. The shock years refer to the years when bird, fish, and invertebrate species were newly added to ESA protection, with data directly sourced from the ESA website. Water and land area data are derived from the census, while data on total employment, GDP in current dollars, and average personal income per county-year are obtained from BEA. The figure shows the trends for each county before and after treatment, with the blue line representing pre-treatment trends and the red line indicating post-treatment trends. Vertical bars depict 95% confidence intervals, with standard errors clustered at the state level.

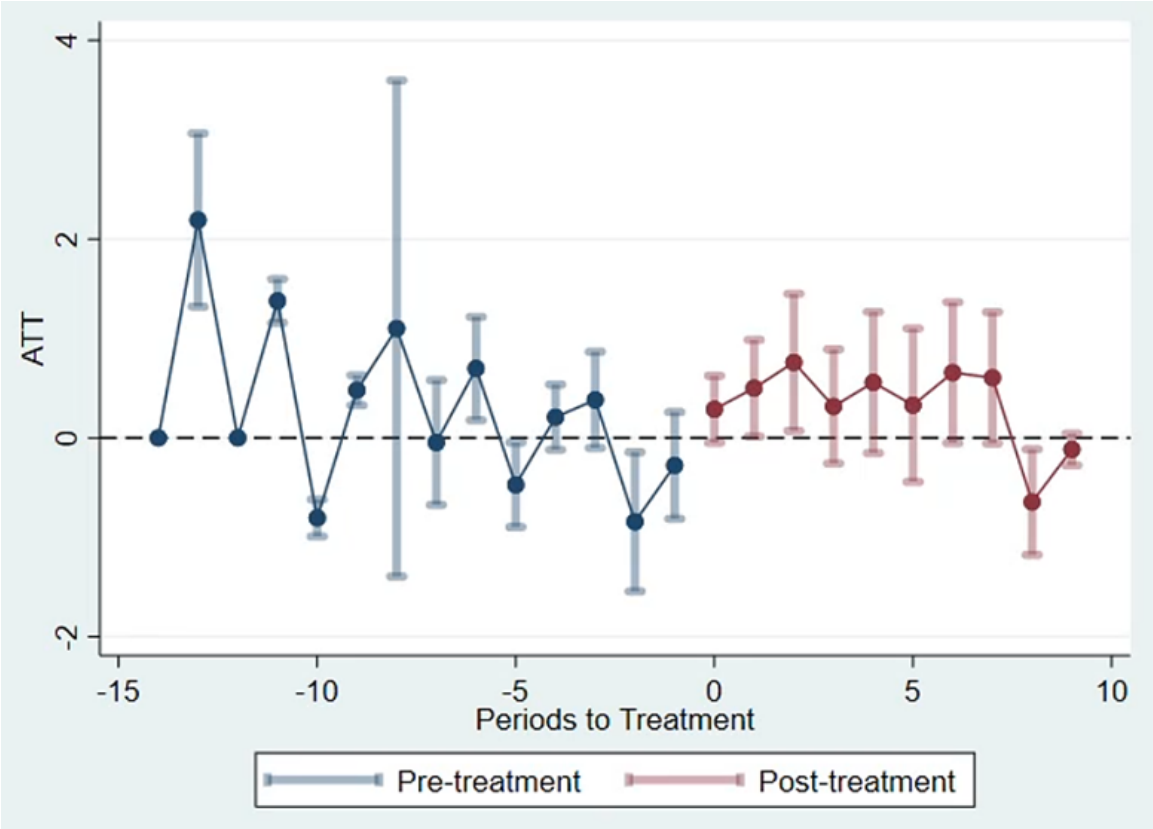


Figure 11: Parallel Trend on Bird Biodiversity

Note: This figure presents a parallel trends test based on the staggered difference-in-differences (DID) method as outlined by Callaway (2021). The data are organized at the county-year level. The figure is derived from our analysis of the processed bird biodiversity index, which utilizes the staggered DID approach, with data units corresponding to county-year observations. The analysis is based on a custom-constructed annual average bird biodiversity index that accounts for the impact of biodiversity within each county and includes a three-year lag to observe long-term effects. The figure illustrates the trend in bird biodiversity across counties following the addition of new species to the ESA protection list. The data are also clustered at the state level to account for within-state correlations. Control variables include water area, land area, total employment, GDP, and personal income, all aimed at controlling for other factors that might influence bird biodiversity. The shock years refer to the years when bird, fish, and invertebrate species were newly added to ESA protection, with data directly sourced from the ESA website. Water and land area data are derived from the census, while data on total employment, GDP in current dollars, and average personal income per county-year are obtained from BEA. The figure shows the trends for each county before and after treatment, with the blue line representing pre-treatment trends and the red line indicating post-treatment trends. Vertical bars depict 95% confidence intervals, with standard errors clustered at the state level.

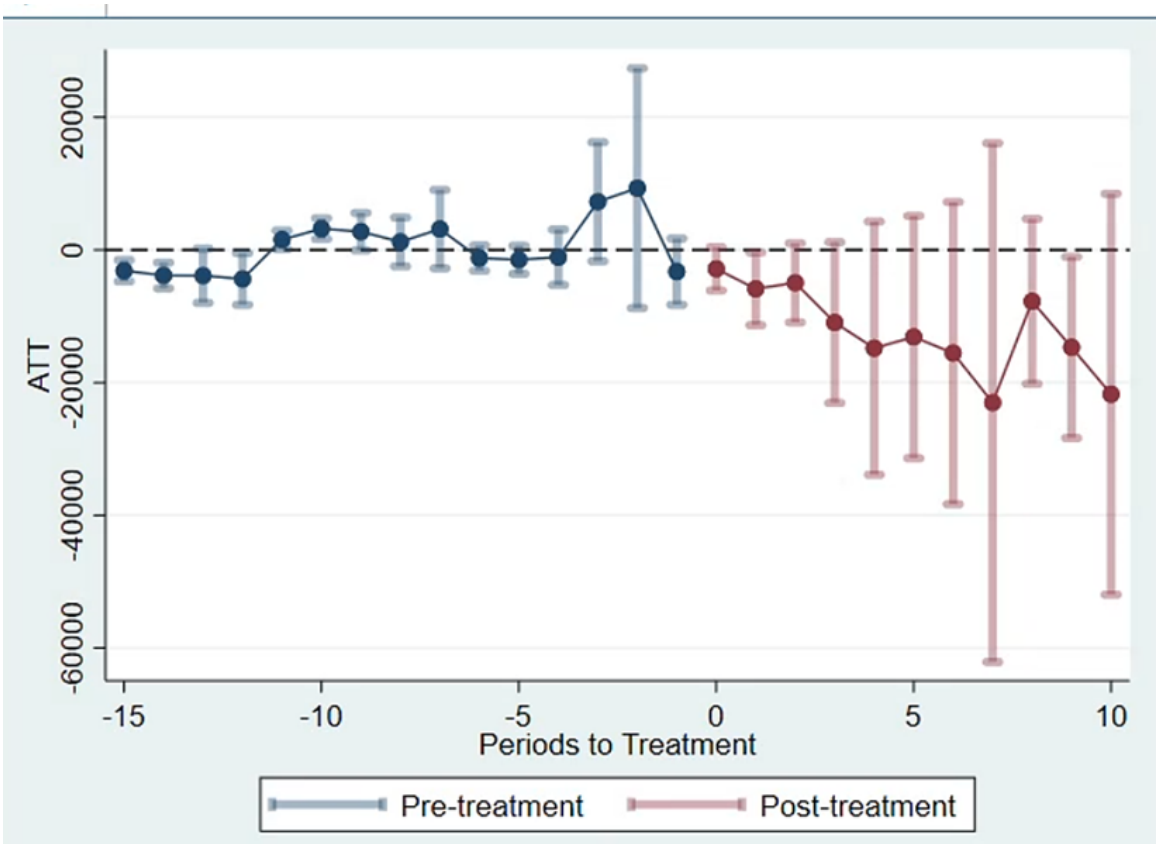


Figure 12: Event Plot of the Regulations on Single-Family Residences

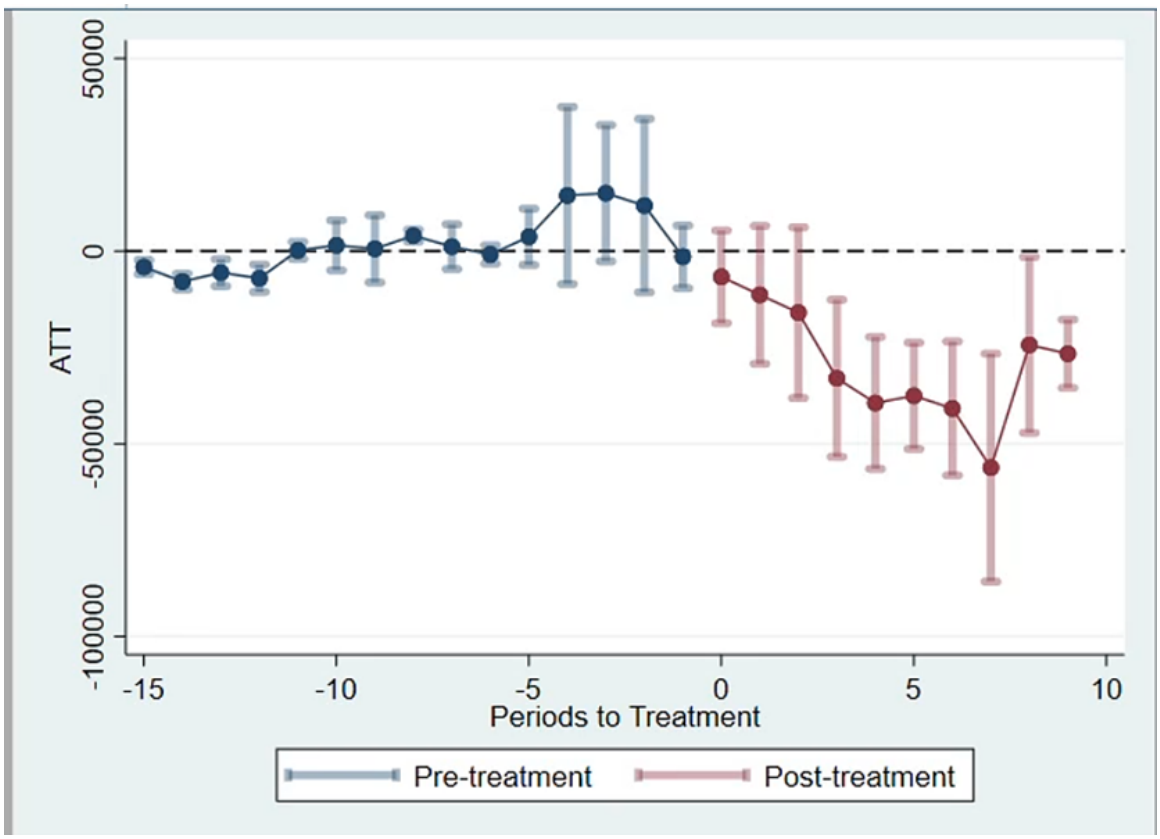


Figure 13: Event Plot of the Regulations on Condominiums

Appendix B Tables

Table B.1: Variable Description

Variable	Definition
Yield	The paper utilizes yield data at two levels: (1) Bond-level yield, defined as the yield to maturity (YTM) based on individual bond-month transactions. This yield is calculated by weighting the yield of each transaction by its transaction volume to obtain the monthly volume-weighted average yield. (2) County-level annual average yield, computed by averaging the monthly yields of all bonds within the same county. Data is sourced from the SDC database.
Years to Maturity (YTM)	Refers to the number of years from the last transaction date of a bond within a given bond-year-month to its maturity date. The data is extracted from the SDC database.
Moody's Rating (MOODY_RATING)	The credit ratings of municipal bonds are based on Moody's rating scale, with ratings encoded numerically from 'C' (1) to 'Aaa' (21). Special notations include 'NP' (0) for Not Prime and 'NR' for Not Rated. This variable categorizes the credit quality of the bonds.
Water_Area and Land_Area	Represents the water and land areas at the county level, with data sourced from the U.S. Census Bureau. The data is reported annually at the county level.
Total Employment, GDP, Personal Income	These variables respectively represent total local employment, Gross Domestic Product (GDP), and per capita personal income. The data is presented on a county-year basis and is sourced from the Bureau of Economic Analysis (BEA) database.
Awareness	Based on petitions filed under the Endangered Species Act (ESA) to list or delist species. This variable aggregates the petitions by county and month, reflecting awareness levels of environmental issues in the respective regions.
Biodiversity	Refers to the adjusted monthly biodiversity index, with data presented at the county-month level. This variable was previously discussed in Figure 1 of the analysis.
Employment (NETS)^{Ave}	Sourced from the NETS database, which provides various employment estimates. This study uses only actual reported employment figures to calculate the average annual employment per county. The data is recorded at the county-year level.
SFR and Condo Housing Prices	The data comes from Zillow's housing price indexes, covering three aspects: (1) Median housing prices for SFR & Condo at the county-month level, (2) Median prices for Single Family Residences (SFR), and (3) Median prices for Condos. These indexes are reported monthly at the county-year level.
Prob. of Issuance & Amount of Issuance	Denotes the probability and total volume of municipal bond issuances in a given county and month. The issuance probability is marked as 1 if bonds were issued during the month and 0 otherwise. The volume represents the aggregate value of all bonds issued within that county-month. Data is sourced from the SDC database.
Prob. of Issuance & Amount of Issuance for GO Bond	Similar to the municipal bond issuance variables, this specifically pertains to General Obligation (GO) bonds. The data is reported at the county-month level and is sourced from the SDC database.
Flood Risk Data	Downloaded from the dataset by Giglio et al. (2021), this data serves as a proxy for the physical risk of flooding or sea-level rise at the county level. Variables include the average flood risk rate (Avg_Flooding_Risk_Rate) and the total flood risk rate (Sum_Flooding_Risk_Rate) within a county.

Table B.2: Classification of Petition Goals

Category	Types of Petitions
Delisting	Delisting: Due to error - Not a listable entity; Delisting: Due to error - New information; Delisting: Species does not meet the definition of an endangered species or a threatened species - Recovered; Delisting: Recovery.
Listing	Listing: Similarity of appearance; Listing: Threatened; Listing: Threatened or Endangered; Listing: Endangered.
Reclassify	Reclassify: Downlist Threatened; Reclassify: Uplist Endangered.
APA	APA: Revise recovery plan; APA: Promulgate new special 4(d) rule; APA: Designate an Experimental population; APA: Other; APA: Designate Critical Habitat.

Appendix C eBird Data

The bird biodiversity measures in this study are constructed based on the eBird dataset, a comprehensive, global citizen science initiative managed by the Cornell Lab of Ornithology (Sullivan et al., 2014). Launched in 2002, eBird compiles bird checklists from diverse locations and dates, serving as one of the primary sources of large-scale, real-time bird observation data for thousands of species worldwide, including over 900 species regularly observed in the United States. As of 2023, eBird houses more than 1 billion bird observations globally, contributed by over 700,000 participants across all countries. Its vast spatial and temporal coverage provides a comprehensive view of biodiversity trends across different regions and time periods. Consequently, this extensive dataset has become widely utilized in various scientific fields, including ecological research, conservation biology, and increasingly in interdisciplinary studies (La Sorte et al., 2017; Horns et al., 2018; Liang et al., 2020).

The data collection process in eBird is designed to be both flexible and standardized. Volunteer birdwatchers (or observers) use standardized protocols to record species, counts of birds seen and/or heard during their birdwatching activities, as well as the date, time, and location, typically using GPS-enabled mobile applications or web interfaces. Each submission, referred to as a "checklist," represents a unique birding event and may include additional information such as breeding behavior, habitat details, and observer effort (e.g., duration, distance traveled). Importantly, each checklist is marked as either “complete” or “incomplete” by the submitting observers. This distinction indicates whether they are submitting a complete list of all birds seen during their observation period, which is crucial for inferring species absences in subsequent analysis. An example of a checklist can be found in Appendix figures **??** and **??**.

Observers use various checklist protocols (e.g., traveling, stationary, historical, incidental) to record their observations, allowing for the aggregation of data ranging from causal bird lists to highly structured surveys. This standardized yet flexible approach enables eBird to accommodate diverse birding practices while maintaining data consistency. The comprehensive data collection method allows for continuous monitoring of bird populations across seasons and locations, providing a rich resource for scientific research and conservation efforts.

To ensure data quality, eBird employs a multi-tiered validation process. Automated filters first flag unusual or unexpected observations based on species, spatiotemporal location, date, and count. These flagged submissions are then reviewed by an extensive network of regional experts before being accepted into the dataset. This rigorous approach, combining automated screening with expert review, helps maintain the integrity and reliability of the data (Kelling et al., 2015; Sullivan et al., 2014).

Endogeneity Issues of Bird Measures .
Despite eBird's implementation of various quality control measures, the nature of citizen science data collection introduces potential endogeneity issues that require careful consideration in our analysis (Callaghan et al., 2017, 2021; Boakes et al., 2010). These issues primarily stem from two features of eBird data, which are also common to similar bird survey datasets. The first critical issue pertains to the potential variation in detection probability across regions. Like all other bird surveys, eBird data does not capture every bird present in a sampling area. This imperfect detection is influenced by various factors such as species' behavior, habitat characteristics, time of day, and weather conditions (Hudson et al., 2017; Johnson, 2008). The second key concern arises from eBird's reliance on a diverse pool of volunteer observers with varying levels of expertise. This heterogeneity in observer birdwatching skills, efforts and preferences can result in inconsistent species identification and count accuracy across different spatial and temporal contexts (Callaghan et al., 2017, 2021). These factors could introduce endogeneity in our biodiversity measures, as observed changes might be partially attributed to variations in sampling effort or environmental conditions rather than actual population dynamics.

It is worth noting that the potential representativeness issues in eBird data, while significant for studies aiming to depict precise bird population trends, are generally less severe in our case of examining the implications of biodiversity on municipal bonds and local government fiscal decisions. Our empirical strategy employs a flexible set of location and temporal fixed effects, effectively comparing biodiversity impacts across time within municipalities. This approach helps mitigate many potential biases, as our estimates would be affected only if detectability varies significantly across time and locations within the same municipality in ways that correlate with changes in municipal bond characteristics or local fiscal decisions.

Nevertheless, we acknowledge that some potential biases could persist, particularly in certain scenarios. For instance, in municipalities with easily accessible or tourist-attractive locations, our biodiversity measures might be skewed due to higher bird reporting rates. This issue could be especially relevant for areas where eco-tourism or bird-watching are significant economic factors. In such cases, changes in biodiversity measures might correlate with economic factors that also influence municipal bonds or fiscal decisions, potentially introducing bias to our estimates despite our fixed effects approach.

To address these potential biases, we employ a multi-faceted approach. First, we mitigate noisy observations by limiting our sample. Specifically, we conduct robustness checks by excluding the early period of eBird data (2002-2005), when total observations were limited and potentially more susceptible to endogeneity issues. Additionally, we exclude records submitted in tourist-dominated municipalities, such as those containing national park destinations, to reduce the impacts

of disproportionate reporting rates in areas with high eco-tourism activity. Our findings on the relationship between biodiversity and municipal bond outcomes remain consistent across these specifications, suggesting that the aforementioned representativeness issues do not substantially impact our results.

Furthermore, we employ a method to adjust for birdwatching effort and detectability probability of birds, using hierarchical approaches commonly applied in biodiversity research (Callaghan et al., 2021; Liang et al., 2020; Sauer and Link, 2011). This adjustment is conceptually similar to the quasi-structural method used by Lerner and Seru (2022) to address endogeneity issues in patent citations. By incorporating these sophisticated techniques, we aim to provide a more comprehensive and robust analysis of the relationship between biodiversity and municipal finance outcomes. Specifically, we model bird counts in the eBird data as an overdispersed Poisson process, jointly determined by birdwatching effort, detectability probability of bird species, true bird abundance, and a random error component. This can be expressed as:

$$\#birds\ observed = \exp^{f(effort,\ detectability,\ abundance,\ \epsilon)}$$

which is equivalent to the following log-linearized model:

$$log(\#birds\ observed) = \beta_0 + \beta_1 effort\ (\#observer,\ duration,\ distance) + \alpha_h + \alpha_{cmy} + \epsilon$$

Here, ϵ reflects variability in observer expertise, consistent preferences in birdwatching, and idiosyncratic shocks in birdwatching trips. We use the distance and duration of each trip as proxies for birdwatching effort from the eBird checklists. We also consider the number of people in the group to address observation intensity. Due to the lack of comprehensive data on detectability rates across survey routes, we use hour-of-day fixed effects, α_h to account for common patterns across hours within a day, such as average bird detectability or ability to observe birds in day versus night. It is worth noting that the functional form of birdwatching effort and detectability could be flexible when considering the interaction of its components. We implement a flexible specification that incorporates additional controls and employs data-driven variable selection, utilizing a large set of potential effort variables. These include the interaction terms of number of observers, duration and distance of each birdwatching trip, additional checklist characteristics, weather conditions (e.g., presence of rain), habitat types, and other relevant factors that could influence bird observations. These controls address differential bird activity or observer ability to detect birds depending on various conditions, thereby addressing different margins for how birdwatching observers can affect the number of birds they see per trip.

Our primary interest lies in the county-month-year fixed effects, α_{cmy}, which capture bird abundance at this level after conditioning on birdwatching efforts and other confounding factors that affect detectability. By recovering the county-month-year fixed effects from this equation, we obtain measures of bird abundance for each county-month-year combination, adjusted for observer effort and other

confounding factors. This adjustment allows us to disentangle the effects of observer effort and preferences from true bird abundance, yielding a more accurate representation of bird populations across different spatial and temporal scales.

Table 1 explores the bird biodiversity relationship with economic fundamentals through both time and cross sectional dimension. In both columns (1) and (2), our regressions show that our proposed bird biodiversity has low correlation with physical risk measure like flooding risk measure from Giglio et al. (2021). However, this proposed variable is endogenous to some economic fundamental like regional total employment. The endogeneity stems from the intuition that for the area with more employment, the self-reported bird trajectory is easier to acquire. What's more, in order to show our measure variation with alternative either biodiversity or economic confounding variables, we also compare the similarities of our bird index with Giglio et al. (2023) spatial exposure across regions. Table 1 shows the cross comparisons between existant measures and our proposed bird biodiversity. We find that most of the measures from Giglio et al. (2023) have lower relationship with our proposed bird biodiversity index. As for the value of our proposed bird biodiveristy, first, from the time varying effect perspective, our measure is more time-varying which helps us to capture biodiversity changes instantaneously. Moreover, in Figure **??**, we find that there is a clear upward trend for the within county variations. This illustrates that for biodiversity trends, there exists strong time-varying volatility for the cross-county measures.