Biodiversity Protection Policy and Housing Markets: Supply, Demand, and Speculation*

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Abstract

Government financing and regulatory actions have been pledged to address biodiversity loss, yet their economic impacts remain unclear. We construct a county-level measure of exposure to potential conservation efforts. Exploiting the 30×30 initiative as a plausibly exogenous shock, we find that a one standard deviation increase in regulatory risk increases house prices by 0.6%. Effects are weaker in counties reliant on nature-intensive industries, but stronger in land-abundant counties, where supply is more elastic and demand for nature amenities is high. Speculative behavior magnifies the price increase. Overall, conservation policies satisfy nature demand but entail trade-offs for growth and housing affordability.

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1 Introduction

Human activity is pushing more species toward global extinction than at any other point in history (Díaz et al. (2019)).[1] This profound loss of biodiversity is likely to impact the quality of life for billions of people and is expected to significantly affect the structure and performance of the global economy (Pereira et al. (2024), WEF (2020)).[2] These consequences have drawn the attention of governments worldwide, which have committed increasing capital to conservation.[3]

Despite this substantial financing, the ultimate economic impact of conservation policy is ambiguous. Protecting land and species can restrict the supply of land, enhance local amenities, and reshape local economies. These forces can work in opposite directions; some generate benefits through improved environmental and amenity value, while others impose costs by constraining land use or restricting nature-intensive industries. Understanding which of these channels dominates is critical for policymakers. For example, rising prices in conserved areas could be misread as evidence of successful investment satisfying local demand, when instead it reflects tighter supply or speculation. Furthermore, even if policymakers observe a positive average effect, impacts are likely to differ across regions depending on economic structure, land availability, and demand for nature.

The central challenge in studying these issues arises from the endogeneity of conservation policies. Thus, the effects are difficult to disentangle without an exogenous shock. We address this challenge by leveraging the Biden administration's 30×30 initiative to causally identify the impact of conservation efforts. On January 27, 2021, seven days into his administration, President Biden signed Executive Order 14008, the most ambitious land conservation program in United States history, aiming to conserve 30 percent of land and water by 2030. We focus our analysis

[1] Extinction rates are now estimated to be 10 to 100 times higher than the historical average over the past 10 million years (Marques et al. (2019)) and nearly a quarter of all animal and plant species are at risk, with wildlife populations having declined by 69% since 1970 (Fund (2020)).

[2] For example, Jones et al. (2018) estimate that one third of land is under intense human pressure, and Johnson et al. (2021) estimate that the continued decline in biodiversity and ecosystem services could reduce global GDP by approximately 2.3% per year by 2030. Specific examples of biodiversity loss causing physical and economic costs include Frank and Sudarshan (2024) and Frank (2024).

[3] Currently, around $204 billion is allocated to biodiversity finance (Bromley (2024)).

on housing markets, since house prices embed both the amenity value of nearby conservation, and the costs of reductions in land availability and lost economic activity. In addition, housing is particularly susceptible to speculation. Extrapolation of past price increases or disagreement about fundamentals may lead investors to bid up properties or land in exposed areas, amplifying price movements beyond fundamentals (Gao et al. (2020), Nathanson and Zwick (2018), DeFusco et al. (2022)).[4]

We use granular ecological data to construct a systematic measure of biodiversity regulatory risk across the entire continental U.S. housing market. Our key measure is protection-weighted range-size rarity (PWRSR), which captures both the rarity of species and, importantly for our analysis, the degree to which habitat still lacks protection. Aggregated to the county level for our analysis, PWRSR captures areas where future interventions, such as land conservation, investment into nature, or restrictions on resource extraction, are most likely.

We implement a difference-in-differences approach using both a discrete and continuous measure of exposure. Anticipated regulation leads to a significant increase in house prices. In our preferred specification, counties in the top tercile of exposure experience a 2.3% increase in house prices compared to counties in the bottom tercile, while a one standard deviation increase in exposure is associated with a 0.6% increase. The dynamics show no significant pre-trends. Following the signing of the order, house prices in treated counties steadily diverge from those in untreated counties, reaching a 3.7% difference by the end of the sample.

The positive and significant effect on house prices is robust to alternative definitions of treatment, varying control sets, and fixed effects specifications, as well as controls for climate exposure. One potential concern is that our measure is correlated with the impact of COVID-19. We address this issue in several ways. First, we include controls to address potential COVID related effects. These include the total park area in a county, the prevalence of working from home, net county migration, and monthly COVID infections, which have been shown to capture the effect of COVID-

[4] Markets may not even fully incorporate conservation risk at the local level due to frictions such as high transaction costs, illiquidity, and limits to arbitrage, making it difficult for buyers and sellers to fully price risk (Case and Shiller (1988), Piazzesi and Schneider (2016)).

19 on house prices (Yap et al. (2022), Gupta et al. (2022), Gustafson et al. (2023)). Second, our largest price increase occurs after 2021 and continues through 2024. Previous research finds that the greatest effects of COVID-19 occurred in 2020, and the main effects on house prices had dissipated by the second quarter of that year (Gupta et al., 2022). Further, we find that the dynamics of the work from home measure and the dynamics for existing park area are significantly different from our measure, with their largest impacts occurring before our shock. Including an interaction term between our measure and work from home or park area is also statistically insignificant. We also proxy for existing nature by using a measure of all biodiversity and find that our effect is only driven by the unprotected component exposed to regulatory risk. Third, we find no effect of biodiversity regulatory risk on rents, whereas COVID had a large effect on rents (Gupta et al., 2022). Fourth, we find a reversal upon the election of President Trump which further suggests a biodiversity regulatory risk effect and not an effect stemming from COVID-19. Finally, we perform a robustness check for omitted variable bias as suggested by Oster (2019) and find that our estimates are extremely robust.

While on average biodiversity regulatory risk leads to rising prices, we find considerable heterogeneity exists across counties. The increase in house prices is smaller in counties heavily reliant on nature-intensive industries, consistent with concerns about stranded assets and local economic costs.

We also explore what channel drives the increase in prices, supply or demand. There is a statistically significant effect in land constrained areas indicating a supply channel. However, effects are strongest in land-abundant areas, where conservation is less likely to bind supply but where demand for nature is high. Consistent with a strong demand effect, we document a post-2021 increase in attention to investments in surrounding natural infrastructure, particularly in connection with the 30×30 initiative. Using a direct measure of demand, we also find that park visitation increased significantly after 2021, suggesting a significant role of demand in driving price responses.

Although supply constraints and demand for nature amenities help explain rising house prices, the magnitude of our estimated effects and the uncertainty of our policy shock suggest an additional mechanism: speculation. Gao et al. (2020), Nathanson and Zwick (2018) and DeFusco et al. (2022) show how speculation can amplify housing market fluctuations. Nathanson and Zwick (2018) emphasize that speculation tends to occur in areas with lots of available land, as investors buy undeveloped parcels, which are cheaper and easier to hold than homes. Gao et al. (2020) uses Home Mortgage Disclosure Act (HMDA) data to identify speculative activity, arguing that purchasing a non-owner-occupied home is more likely to be driven by speculative motives.

Speculation appears to play a key role in amplifying housing price responses to biodiversity regulatory risk. We find an increase in investment borrowing and a larger increase in land values compared to property values. Using HMDA loan-level data, disaggregated by loan purpose, we find that while both the number and value of loans increase for all loan types, effects are strongest for investment loans, consistent with speculative buying. For a one standard deviation increase in exposure in Quartile 4, primary residential loan applications increase by 1.1%, while investment loans increase by 4.6%. Using land and property values from Davis et al. (2021), we find that conservation effects are much stronger for land values than for property values. For a given increase in exposure, land values rise 1.5 times as much as property values.

The role of speculation is particularly salient given the volatile policy environment. Climate policy has been characterized by high uncertainty and repeated enactments and reversals over the past two decades (Bolton and Kacperczyk (2021), Ilhan et al. (2021), Seltzer et al. (2022), Barnett (2024), Basaglia et al. (2025), Delis et al. (2019), Noailly et al. (2022)), and there is a high likelihood that biodiversity policy will follow a similar trajectory. Indeed, we provide evidence that the 2024 election of President Trump reverses both the policy direction and our estimated effects. Taken together, our evidence on speculation and policy reversals suggests a high likelihood of successive speculative booms and busts in housing markets exposed to biodiversity regulatory risk.

Our findings make four contributions to the literature. First, we provide the first systematic study of biodiversity-related regulatory risk in housing markets. While prior work shows that climate risk is priced in housing markets (Bernstein et al. (2019), Seltzer et al. (2022), Ilhan et al. (2021), Bolton and Kacperczyk (2021), Hsu et al. (2023), Goldsmith-Pinkham et al. (2023), Acharya et al. (2022), Baldauf et al. (2020)), very little work has examined biodiversity, despite its importance as a distinct environmental risk. Second, we address the endogeneity of conservation policy by exploiting an exogenous policy shock. This allows us to causally identify the effect of anticipated conservation. Third, we provide evidence for which channels biodiversity regulatory risk impacts house prices, showing that the price increase has significant heterogeneity and a strong demand component, distinguishing our study from recent work (Bahrami et al. (2024), Frank et al. (2025), Cornaggia et al. (2025)). These channels highlight important policy trade-offs. Conservation can increase welfare by preserving biodiversity and satisfying demand for natural amenities, but it also risks depressing values in nature-intensive economies and raising housing costs. Fourth, we highlight the role of speculation in amplifying policy shocks. We show that extrapolative demand and anticipation of conservation not only raise house prices but also amplify increases beyond fundamentals. Together, these contributions establish biodiversity as a distinct, financially material risk in housing, clarify the channels through which conservation affects asset prices, and underscore how speculation can magnify policy shocks, with implications for housing affordability and economic growth.

2 Literature Review

There is a nascent literature on biodiversity in finance, which examines the measurement of biodiversity-related risk, its effects on stock returns, and the financing of biodiversity projects (Giglio et al. (2023), Garel et al. (2024), Flammer et al. (2025), Karolyi and Tobin-de la Puente (2023)). No work yet exists that evaluates biodiversity regulatory risk on housing as an asset class. Pena et al. (2024) also use NatureServe data merged with firm locations to assess the impact of biodiversity regulatory risk on firm outcomes.

Other papers have investigated the impact of restrictions from already implemented land conservation on land values. Frank et al. (2025) show that the Fish & Wildlife Service takes into account local housing market areas before determining critical habitat for species under the Endangered Species Act (ESA). They find little evidence that land supply is being constrained due to ESA actions. Grupp et al. (2023) do not find any effect of land protection on vegetation and night-lights. Cornaggia et al. (2025) use property level data to show that county level species richness is correlated with higher sales prices. Bahrami et al. (2024) implements a regression discontinuity near areas that select into being protected and finds a large discount in prices for those in protected areas. Our study is complementary to their work in several ways. First, while prior work focuses on the effects of land restrictions within protected areas, we examine a broader range of conservation impacts on housing markets. Government actions extend beyond land use restrictions, including investment into nature and restrictions on industrial activity. We show that this natural investment as well as potential economic damage are capitalized in house prices. Second, while regression discontinuity provides valuable evidence on localized land-use restrictions and offers sharp identification of those effects, our difference-in-differences is designed to capture aggregate market responses, including general economic and amenity effects that boundary comparisons may not detect. The different focus helps explain why our findings differ from those of Bahrami et al. (2024). Third, we focus on currently unprotected areas that have a high likelihood of receiving some form of regulatory action. This is significantly different from previous papers, which study already implemented protection policies. Fourth, we overcome endogeneity issues by focusing on the most ambitious land conservation plan envisioned in the history of the United States. Finally, we provide novel evidence that biodiversity conservation can fulfill demand for nature but has trade-offs.

We also relate to climate finance papers that evaluate the impact of climate-related risks on house prices. For example, a series of articles evaluate the risk of floods from rising sea levels and their impacts on house prices (Baldauf et al. (2020), Bernstein et al. (2019)). Other articles in economics and finance have investigated a myriad of environmental factors affecting house prices, such as air quality (Smith and Huang (1995), Chay and Greenstone (2005), Bayer et al. (2009)), heat waves (Addoum et al. (2024)), lead remediation (Billings and Schnepel (2017)), hazardous waste remediation (Greenstone and Gallagher (2008)), toxic plant openings and closings (Carroll (2003)), carcinogenic risk (van Binsbergen et al. (2024)), and general climate change (Giglio et al. (2021)). We contribute to this literature by showing that other risks related to ESG, in this case, the impact of government efforts to protect biodiversity, affect house prices.

We also contribute to the literature on housing speculation. Previous work has shown the importance of non-occupant home buyers and speculation in the housing market (Gao et al. (2020), Bayer et al. (2020), Mian and Sufi (2022), DeFusco et al. (2022), Nathanson and Zwick (2018)). We complement this work by documenting that regulatory risk, and in particular biodiversity related regulatory risk can fuel speculative buying in housing markets.

3 Institutional Details

Modern federal interest in species protection can be traced back to the environmental movement of the 1960s. A growing concern for biodiversity and environmental protection led to the establishment of the Land and Water Conservation Fund in 1964, which began to purchase land for conservation. A series of Endangered Species Acts were also passed in the 1960s. These acts established the first list of endangered and threatened species and directed government agencies to consider their impact on the environment (Kline (2022)). Finally, in 1970, the Nixon Administration established the Environmental Protection Agency, creating a centralized organization in charge of biodiversity, uniting several disparate efforts at environmental preservation that were underway at the time (Kline (2022)). While the federal government's conservation efforts have waxed and waned with different administrations, there has been a constant undercurrent of activity.

This activity has manifested itself more recently in the 30×30 initiative. In 2019, at the 74th United Nations General Assembly, Costa Rica led a group of countries in forming a coalition for nature policy, calling itself the High Ambition Coalition for Nature and People (for Nature and People (2022)). This coalition proposed an initiative to preserve 30% of Earth's land and marine areas for conservation by 2030. This initiative was adopted by 196 countries and formally incorporated into the Kunming-Montreal Global Biodiversity Framework at the 2022 COP15 conference. The United States joined this commitment on January 27, 2021, when President Biden signed Executive Order 14008, in which Section 216 committed America to preserving 30% of U.S. land and water by 2030, dubbed the America the Beautiful Initiative (Register (2021)).[5]

Following the signing of this initiative, two major legislative actions were taken that included provisions for biodiversity protection, which we use to validate our measure of biodiversity regulatory risk. The first piece of legislation passed November 15th 2021, was the Infrastructure Investment and Jobs Act, also known as the Bipartisan Infrastructure Law (BIL). While primarily an omnibus bill funding a wide range of infrastructure projects, one major category it supported was “Restoration and Resilience" projects (DeFazio, Peter A. (2021)). These projects focused on restoring ecosystems, protecting biodiversity, and increasing recreational value. For example, one project in Kittitas County:

> “has three primary goals: 1) improve access to high quality fishing on BLM lands; 2) restore currently-degraded riparian gallery habitat including invasive species removal and native tree and shrub plantings; and 3) develop off-channel pool areas in the rivers 5 year floodplain."

Around $3.2 billion was allocated to 1,445 different Restoration and Resilience projects around the nation and included as part of the America the Beautiful Initiative. The second major piece of legislation was the Inflation Reduction Act (IRA). Another omnibus bill, the IRA included several sections directed specifically toward conservation and resilience, namely Title II, Subtitle B, and

[5] There were 6 areas of improvement listed as part of the America the Beautiful Initiative - (1) creating more parks and safe outdoor opportunities in nature-deprived communities; (2) supporting Tribally led conservation and restoration priorities; (3) expanding collaborative conservation of fish and wildlife habitats and corridors; (4) increasing access for outdoor recreation; (5) incentivizing and rewarding the voluntary conservation efforts of fishers, ranchers, farmers, and forest owners; (6) creating jobs by investing in restoration and resilience projects and initiatives, including the Civilian Climate Corps. More details can be found at: `https://www.doi.gov/pressreleases/biden-harris-administration-outlines-america-beautiful-initiative`. Furthermore, the order committed "The Secretary of the Interior, in consultation with the Secretary of Agriculture, the Secretary of Commerce, the Chair of the Council on Environmental Quality, and the heads of other relevant agencies, shall submit a report to the Task Force within 90 days of the date of this order recommending steps that the United States should take, working with State, local, Tribal, and territorial governments, agricultural and forest landowners, fishermen, and other key stakeholders, to achieve the goal of conserving at least 30 percent of our lands and waters by 2030."

Title V, Part 2. Approximately $2.6 billion and 814 projects were allocated directly to conservation projects and included as part of the America the Beautiful Initiative.

As discussed in the introduction, with the 2024 election of President Trump, the political landscape of conservation has shifted again. On his first day in office, President Trump rescinded the executive order signed by President Biden that aimed to conserve 30 percent of U.S. land and marine ecosystems. Additionally, while the IRA and BIL remain embedded in legislation, funding was severely restricted. This policy change introduces a new regulatory shock. Although our outcome variable, house prices, moves slowly, we provide suggestive evidence that the effect in treated counties has begun to reverse in the wake of this action. However, as biodiversity continues to decline, regulatory responses will persist mechanically, most notably through the Endangered Species Act (ESA), which will continue to expand as more species are listed. In this context, our results remain relevant for understanding long-term regulatory risk and for informing broader global conservation efforts, such as the Kunming Declaration on Biodiversity, initiatives that are likely to intensify in the future.

4 Data

In this section, we summarize the main data. Table 1 reports summary statistics for our main sample, while Table IA.1 provides variable definitions. Standard datasets are detailed in Table IA.2.

4.1 Biodiversity Measure

Because our central question concerns the conflict between the expected effects of conservation and house prices, prior measures of exposure to biodiversity risk, such as 10-K filings or aggregate media mentions, are inadequate for our purposes. Biodiversity is directly tied to ecosystems and the land they occupy, while housing is also a geographically dependent outcome. Therefore, a proper measure of risk must incorporate the geospatial component of biodiversity. It is also important that our measure excludes already conserved areas, as areas that are already conserved are no longer at risk and would not adequately provide a measure of exposure. This distinction separates our research question from previous studies, which focus on how housing prices respond when building is constrained within already protected areas. Taken together, these considerations motivate our use of a measure that is both geographically varied and characterized by uncertainty, but a high probability of future conservation. In this subsection, we describe the data and how our approach captures geographical exposure to biodiversity regulatory risk.

4.2 NatureServe

We use data on predicted habitat ranges of endangered species from NatureServe, a nonprofit organization that provides high-quality data on species and ecosystems. Through its expertise in species distribution, conservation status assessments, and ecosystem analysis, NatureServe addresses critical data gaps that government agencies alone often cannot fill.

Our paper leverages biodiversity importance measures developed by NatureServe, as outlined in Hamilton et al. (2022). A key innovation of this work is its reliance on machine learning to overcome limitations in previous biodiversity mapping. This study applies Habitat Suitability Models (HSMs) to create high-resolution biodiversity assessments across the contiguous United States, focusing specifically on imperiled species. Their approach begins by using species occurrence data, supplemented with records from natural history collections, citizen science platforms, and regulatory databases. Based on this occurrence data, habitat suitability models were constructed using a random forest machine learning algorithm, trained on high-resolution environmental predictor variables such as topography, climate, soil, hydrology, and land cover. The output was a binary classification of suitable versus unsuitable habitat, which was then standardized to 990-meter grid resolution for spatial aggregation.

From these modeled habitat areas (A_i), conservation priority is measured using Range-Size Rarity (RSR). RSR is defined as:

$$RSR_i = \frac{1}{A_i}$$

where A_i is the total habitat extent of species i. Therefore, species with smaller potential habitat areas are given greater weight in the measure. This improves upon simple species richness, as species with high RSR scores are more vulnerable to single shocks and offer fewer opportunities for conservation intervention. Furthermore, RSR is a commonly used metric in conservation planning (Guerin and Lowe (2015), Jenkins et al. (2015)). However, some species may already be fully protected and therefore do not require additional regulatory action. Therefore, RSR alone may not provide an accurate measure of regulatory risk, overestimating the probability of conservation efforts in areas with significant protection already. RSR is augmented with the current amount of protection to create a more accurate measure.

Protection-Weighted Range-Size Rarity (PWRSR) adjusts RSR to account for the extent to which a species' modeled habitat overlaps with protected areas, defined as GAP-1 or GAP-2 designated areas. Thus, for a particular species, PWRSR is defined as:

$$PWRSR_i = RSR_i * (1 - P_i)$$

where P_i is the fraction of the species' habitat that falls within protected areas. PWRSR provides a more accurate measure of conservation priority.

Finally, PWRSR values were summed across all species i within each 990-m grid cell, creating a continuous measure of biodiversity importance:

$$PWRSR_g = \sum_{i=1}^{I} PWRSR_i$$

Some policymakers may prefer a binary classification—indicating whether or not an area should be preserved, rather than a continuous measure, for ease of interpretation and use. Therefore, a final metric called Areas of Unprotected Biodiversity (AUBI) is constructed. The AUBI variable takes a value of 1 if the PWRSR of a grid cell exceeds 0.0005. These areas represent concentrations of rare but unprotected species, highlighting locations where regulators may wish to focus biodiversity protection efforts. We graph our PWRSR measures as well as AUBI in Figure IA.1.

While PWRSR and AUBI are fine-grained measures at the 990 m grid level, this granularity is most useful for ecological studies, species conservation planning, and habitat assessments, contexts where small differences in habitat availability and protection status are significant. Yet this level of detail, while valuable to biologists and conservation planners, may not be meaningful for regulatory risk assessment. Unlike flood risk maps, where localized exposure matters directly to landowners and infrastructure projects, biodiversity regulation is typically implemented at a broader administrative level, such as counties or regions. Furthermore, these regulations and investments affect housing at a more aggregate level as well. Amenity and economic effects are dispersed across geographical regions and do not necessarily fall directly along grid level distinctions. To address this concern, we aggregate both the PWRSR and AUBI measures to the county level for our main analysis. We calculate the area-weighted mean for each measure. Letting A_g denote the total area of grid cell g within county C, we define county-level PWRSR and AUBI as:

$$PWRSR_C = \frac{\sum_{g \in C} PWRSR_g \times A_g}{\sum_{g \in C} A_g}$$

$$AUBI_C = \frac{\sum_{g \in C} AUBI_g \times A_g}{\sum_{g \in C} A_g}$$

Our analysis uses both the continuous PWRSR and AUBI measures, as well as a binary treatment indicator defined as being in the top tercile of either AUBI or PWRSR. Figure 1 displays our county-level PWRSR and AUBI measures. In Section 5.1, we show that this measure accurately captures future government action to protect biodiversity. This measure enables future research in finance to capture biodiversity risk that is missed by previous non-spatial or proxy-based approaches.

4.3 Controls

A potential concern is that areas with high conservation risk may also be exposed to other climatic or geographic risks that could confound our measure. To control for this possibility, we again rely on data from NatureServe. We utilize two geographical datasets from NatureServe: the Climate Change Exposure Score and the Habitat Climate Change Vulnerability Index (HCCVI). The Climate Change Exposure Score measures the degree of stress imposed by climate change on ecosystem processes by examining shifts in temperature and precipitation patterns. It integrates baseline conditions, historical variability, and future projections to assess deviations from historical norms. This metric is derived from two components: Climate Departure, which forecasts changes in temperature and precipitation from mid-20th century averages to future scenarios, and Climate Sensitivity, which evaluates alterations in modeled habitat suitability over time. Appendix Figure IA.2 presents the geographic distribution of climate change exposure.

The Habitat Climate Change Vulnerability Index (HCCVI) score quantifies the vulnerability of various habitats within a 7-square-mile hexagonal grid. Higher HCCVI scores indicate lower vulnerability whereas lower scores suggest higher vulnerability. We aggregate both measures to the county level using the same area-weighted approach applied to PWRSR and AUBI. Appendix Figure IA.3 presents the geographic distribution of the measure.

An additional concern is that our conservation exposure measure could be correlated with areas that experienced housing price increases during the COVID-19 pandemic. We address this in several ways. First, We include several controls to account for potential COVID-related influences on housing prices. All regressions include the total park area within a county as a control variable. This accounts for the increased value of existing natural investments, which have been shown to increase housing prices during the COVID-19 pandemic (Yap et al. (2022)). Second, we construct a work-from-home measure following Dingel and Neiman (2020). We include this control for the prevalence of remote work in all of our regressions. Work from home has also been shown to capture the impact of COVID-19 on house prices (Gupta et al. (2022), Mondragon and Wieland (2022)). Furthermore, while currently existing nature investments drove house price increases during the pandemic, in a later section we show that our effects originate in nature-deprived areas that anticipate future investments into environmental projects.

4.4 Balance Panel

We also test whether our measure of biodiversity exposure is plausibly exogenous and broadly uncorrelated with other county level characteristics. We regress our exposure measures on a set of control variables: HCCVI, Climate Change Exposure (both near- and mid-century), prevalence of remote work, one month lagged log of employment, total park area, percent urban area, log of land area, log of water area, and log of local GDP. We also include in one specification, state fixed effects. Results are presented in Table 2. In the first two columns, the only highly significant regression variables are $Ln(Land\ Area)$ as well as $Total\ Park\ Area\ Percent(\%)$, which we include in our regressions, and later use to demonstrate the channel of the effect. Moreover, the R^2 values from these regressions are low, approximately 8%. This suggests that little of the variation is explained by county-level characteristics, supporting the assumption that our exposure measure is as-good-as-random.[6]

5 Results

5.1 Validation of AUBI Measure and Government Conservation Projects

In this section, we show that our biodiversity measure serves as a valid proxy for regulatory risk. We compile data on conservation projects initiated after our policy shock, including their geographic centers, funding levels, and project classifications.

Appendix Table IA.3 reports summary statistics for these projects. The first column presents aggregate program statistics. A total of 2,112 projects were launched under the IRA and BIL, with approximately $6 billion in funding. We define conservation projects as those categorized under "Resilience and Ecosystem Restoration," "America the Beautiful Challenge Grants," or with "Conservation" in the program name within the classification. These conservation projects account for roughly 33% of the total number of projects and about 20% of the total funding.

[6]Another potential concern about random assignment is that households may have anticipated future conservation actions and selectively relocated to counties with high values of AUBI or PWRSR. However, the NatureServe data underlying our measure were only made publicly available in 2020, mitigating this concern.

We examine the proportion of project centroids that fall within AUBI-designated areas. In the column labeled "$<$ 2km," we expand the boundary of each AUBI grid cell by 1 km in all directions. We then calculate both the number and proportion of project centroids that fall within an AUBI area. The first two rows show that 18.7% of projects and 20% of funding fall within AUBI-designated grids. We repeat this analysis in the next two columns, expanding the grid boundaries by 4 km and 9 km, respectively. With a 5 km buffer, we find that 37% of all projects and 41% of total funding fall within AUBI grids. Expanding the buffer to 10 km, we observe that 46.6% of all projects and 50.2% of funding fall within AUBI grids. These results provide strong non-parametric evidence that our ex ante AUBI measure predicts ex post regulatory action on conservation projects on a county level. However, while many projects do fall directly within our ABUI grids, a significant portion fall outside and are only near the boundaries. This further motivates our use of a county-level measure, as conservation projects may not fall directly within AUBI areas but are often initiated nearby.

We complement this non-parametric evidence with regression analyses. We construct four outcome variables to assess a county's realization of biodiversity-related regulatory risk under the IRA and BIL. The first outcome variable, $Has\ Project\ (\%)$, is a binary variable equal to 1 if a county receives at least one project and 0 otherwise. The second, $\#\ of\ Projects$, is a count of the total number of projects received by each county. Not all planned projects ultimately receive funding, so we construct two additional measures to capture this distinction. The third outcome variable, $Has\ Funding$, is a binary indicator equal to 1 if a county receives a project that eventually receives funding, and 0 otherwise. The fourth, $Amount\ Funded$ is a continuous variable that represents the total amount of funding allocated to projects within each county.

We regress these outcome variables on four different measures of biodiversity exposure. Specifically, we construct binary indicators equal to 1 if a county is in the top tercile of AUBI or PWRSR exposure, and 0 if it is in the bottom tercile, excluding the middle tercile from the analysis. We also use normalized continuous versions of AUBI and PWRSR exposure using the full sample of counties. Specifically, we estimate the following regression specification:

$$Y_i = \alpha + \beta_1 Exposure_i + \varepsilon \tag{1}$$

Where Y_i is one of the four outcome variables for county i and $Exposure_i$ is one of our four biodiversity exposure measures. Results are presented in Panel A of Table 3.

We find that all of our measures of biodiversity exposure are significant at the one percent level. Counties in the top tercile of AUBI exposure are 1.3 times more likely to receive a project compared to those in the bottom tercile. A similar pattern holds for PWRSR exposure, where counties in the top tercile are also 1.3 times more likely to receive a project. In the continuous specification, a one standard deviation increase in AUBI (PWRSR) exposure is associated with a 3.89 (5.17) percentage point increase in the probability of receiving a project. The second column assesses the intensity of regulatory intervention using the total number of projects received per county. Again, all biodiversity exposure measures are significant at the 1% level. Counties in the top tercile of AUBI and PWRSR exposure receive, on average, 1.8 times more projects than those in the bottom tercile. The third column examines whether announced projects receive funding; here, we do not find a statistically significant relationship with biodiversity exposure. However, the fourth column shows that, conditional on receiving funding, biodiversity exposure significantly predicts higher funding amounts. Counties in the top tercile of AUBI exposure receive over \$1.9 million more in funding than those in the bottom tercile. Counties in the top tercile of PWRSR exposure receive \$2.4 million more. A one standard deviation increase in AUBI (PWRSR) exposure is associated with an additional \$1.2 million (\$1.4 million) in funding.

Taken together, this evidence shows that our ex-ante measure of biodiversity regulatory risk is capturing what we intend. AUBI-designated areas serve as a reliable proxy for regulatory risk. Our analysis shows that these areas are significantly more likely to receive conservation projects and funding under major federal initiatives, confirming that biodiversity regulatory risk translates into tangible government intervention.

We further validate our biodiversity exposure measure using conservation easements initiated after January 2021. A conservation easement is an agreement between a property holder and a land trust or public entity over the rights to use certain parts of the land. For example, instead of buying a forest outright, a land trust can contract with the forest owners to purchase only the extraction rights and set them aside in order to conserve the area. We use data from the National Conservation Easement Database, which includes the geographic boundaries of easements and their stated purposes, such as scenic preservation or wetland protection. We construct four outcome variables to test whether biodiversity exposure predicts regulatory intervention through conservation easements. The first is a binary variable equal to 1 if any part of a county intersects with a conservation easement. The second is a count variable representing the number of unique conservation easements intersecting the county. The third is a binary variable indicating whether a county intersects with an easement specifically classified as conservation-oriented, defined by purposes such as environmental, recreational, or scenic. Finally, the fourth variable counts only conservation-type easements, those with environmental, recreational, or scenic purposes, that intersect a county. We regress each of these four outcomes on the same four biodiversity exposure measures used in prior analyses. The first two are binary indicators equal to 1 if a county is in the top tercile of AUBI or PWRSR exposure. The remaining two use the full sample and the normalized continuous versions of AUBI and PWRSR. Results are reported in Panel B of Table 3.

In the first column, we present how the probability of receiving a conservation easement differs between top tercile and bottom tercile counties. All measures of biodiversity exposure are statistically significant at the 1% level. Counties in the top tercile of AUBI exposure are 10.6 percentage points more likely to receive an easement, while those in the top tercile of PWRSR exposure are 10.35 percentage points more likely. A one standard deviation increase in AUBI (PWRSR) exposure is associated with a 0.66 (0.17) percentage point increase in the likelihood of receiving an easement. The second column presents our results on the intensity of regulatory intervention using the count of easements received per county. Again, we find that all of our measures of biodiversity exposure are significant at the 1% level. Counties in the top tercile of AUBI and PWRSR exposure receive on average, 1.3 times more easements relative to the mean than counties in the bottom tercile. When focusing specifically on conservation projects, the effects become even more pronounced. Counties in the top tercile of AUBI exposure experience a 4.3 percentage point increase in the likelihood of receiving a conservation easement, while those in the top tercile of PWRSR exposure see a 4.9 percentage point increase. These effects represent nearly a doubling of the baseline probability of receiving a conservation easement. In the final column, we measure the intensity of conservation easements and find that the number of conservation easements per county increases by 0.098 for AUBI-treated counties and 0.111 for PWRSR-treated counties. These findings confirm that our ex ante biodiversity regulatory risk measures are strongly associated with actual government action, validating their use as an instrument for the probability of conservation interventions and further supporting our broader analysis of how biodiversity-related regulatory risk affects housing markets.

5.2 AUBI and House Prices

In this section, we begin by estimating the average effect of conservation efforts on housing markets. Specifically, we examine whether counties with higher exposure to the probability of conservation efforts as proxied by unprotected biodiversity, measured using our AUBI (Areas of Unprotected Biodiversity Importance) score, see differential price effects following the signing of Executive Order 14008, which launched the *30 by 30* conservation initiative. We estimate the effect using a difference-in-differences design. We designate as our post event the signing of Executive Order 14008 by President Biden in January 2021, which heightened risk about government led response to biodiversity. Our outcome variable, Y, is the natural logarithm of county-level home prices, measured using Zillow's Home Value Index (ZHVI). On the right-hand side of the equation, we include a treatment indicator based on NatureServe data, equal to 1 for counties in the top tercile of AUBI or PWRSR exposure and 0 for those in the bottom tercile; counties in the middle tercile are excluded from the analysis. We interact the treatment indicator with a post-period dummy variable equal to 1 for dates after January 2021.

We implement the above design using the following specification:

$$ln(price)_{it} = \beta_0 + \beta_1(Treat \times Post)_{it} + \beta_2' X_{it} + \alpha_i + \delta_t + \gamma_{st} + \varepsilon_{it} \quad (2)$$

Here, $\ln(price)_{it}$ denotes the natural logarithm of the Zillow Home Value Index for county i in month t. The variable $(Treat \times Post)_{it}$ represents the interaction between the treatment indicator and the post-period dummy. We include county fixed effects (α_i) to account for time-invariant differences across counties, month fixed effects (δ_t) to capture national housing market trends, and state $\times$ year-month fixed effects (γ_{st}) to absorb state-level time-varying shocks. Our vector of controls (X_{it}) includes: (i) one month lagged log of employment in county i in month t, (ii) total park area in county i $\times$ post, (iii) work-from-home suitability in county i $\times$ post, (iv) two measures of climate change exposure in county i from NatureServe $\times$ post, and (v) habitat climate change vulnerability from NatureServe in county i $\times$ post.

Results are presented in Table 4. Columns (1) and (2) report raw estimates without fixed effects or controls. Columns (3) and (4) add county and month fixed effects. Columns (5) and (6) include the full set of control variables and state $\times$ year-month fixed effects. Our coefficient of interest is β_1. Across all columns, β_1 is positive and statistically significant. In our preferred specification (column 6), we estimate that moving from the bottom tercile to the top tercile of AUBI exposure leads to a 2.3 percent increase in house prices after the shock. Given a median county home value of \$167,000, this effect corresponds to an increase of approximately \$3,841. These findings show that conservation efforts are positively capitalized into house prices.

Table 5 measures the same effect as Table 4, that conservation efforts positively impact house prices. Rather than using a binary treatment definition, we employ continuous measures of biodiversity regulatory risk. This approach allows us to retain the full sample of counties in the analysis. Specifically, we use the PWRSR and AUBI scores as continuous treatment variables. We additionally estimate specifications using the natural logarithm of the exposure variables. Table 5 reports results using the continuous measure. Columns (1) and (2) show raw estimates without fixed effects or control variables. Columns (3) and (4) introduce county and month fixed effects. Columns (5) and (6) add the full set of controls and state $\times$ year-month fixed effects. Columns (7) and (8) include the full set of controls and fixed effects but use the natural logarithm of the AUBI and PWRSR scores in place of their raw values. Across both AUBI and PWRSR specifications, the interaction coefficient remains positive and statistically significant in seven of the eight regressions. In our preferred specification (column 6), a one standard deviation increase in exposure (0.13) is associated with a 0.6% increase in house prices. Given a median county home value of $164,950, this corresponds to a $990 increase in home value. These results demonstrate that the estimated effect is robust across different measures of biodiversity exposure.

Panels A and B of Figure 2 present our dynamic difference-in-differences analysis, which tests the parallel trends assumption and illustrates how the effect of biodiversity regulatory risk on house prices evolves over time. We implement a dynamic version of equation 2. Each coefficient β_{1t} captures the differential change in house prices between treated and untreated counties in month t. We estimate two specifications: one using our AUBI measure and another using our PWRSR measure.

In Panels A and B of Figure 2, there are no significant differences in house price trends between treated and untreated counties prior to January 2021. This supports the parallel trends assumption. Following the policy announcement, however, we observe a steady and statistically significant increase in house prices for treated counties relative to control counties. The effect builds gradually over time and levels off toward the end of the sample period, consistent with delayed price responses in housing markets, which are known to exhibit search frictions and slow-moving adjustments (Case and Shiller (1988), Piazzesi and Schneider (2016)). These findings also confirm that the realization of projects is not driving our main effect. The earliest project was announced in November 2022[7], at which point our effect had reached 113% of its final value. By the end of the sample period, the estimated coefficient on β_{1t} reaches 0.037. This implies that, by the end of the sample period, a county moving from the bottom to the top tercile of biodiversity exposure would

[7] see https://landtrustalliance.org/resources/learn/explore/america-the-beautiful

experience a 3.7% increase in house values, corresponding to approximately $6,104 based on the median home value.

We also conduct the analysis at the MSA level. Specifically, we re-estimate Equation 2 using the MSA-level Zillow Home Value Index. Results are reported in Table IA.4. We also estimate the dynamic difference-in-differences specification in Equation 2 using MSA-level data. Results are presented in Figure IA.4. Across both the static and dynamic specifications, results are consistent with those from the county level analysis, suggesting that our findings are not driven by the level of geographic aggregation. By the end of the sample, house prices in treated MSAs are approximately 4% higher than those in control MSAs.

Figures 2 and IA.4 jointly provide strong visual and statistical evidence that biodiversity-related regulatory risk is capitalized into housing markets, with effects that persist and grow over time. The slow buildup and consistent pattern across geographic levels reinforce the interpretation of the effect as a forward-looking market response to policy risk, rather than a result of short-run shocks or local idiosyncrasies.

5.2.1 COVID-19 and Robustness

The timing of our shock overlaps with the COVID-19 pandemic, raising the concern that counties heavily affected by COVID may be correlated with high biodiversity exposure. In this case, the observed effects could reflect COVID-related housing demand shifts rather than regulatory risk.

To address this possibility, we incorporate several controls that capture channels through which COVID may have affected local housing markets. First, the prevalence of working from home (WFH) has been shown to capture the effect of COVID-19 on house prices (Gupta et al. (2022)), so we include the county-level WFH measure from Dingel and Neiman (2020).[8] Second, access to natural amenities may have become more valuable during the pandemic (Yap et al. (2022)), so we construct a county-level measure of total park area. Third, as Gustafson et al. (2023) emphasize,

[8] Other measures of WFH or COVID-19 dynamics are constructed at a national or state level and would be absorbed by our fixed effects. Furthermore, Kmetz et al. (2023) show that most WFH measures, including ours from Dingel and Neiman (2020), are highly correlated, alleviating concerns about the choice of a particular measure.

pandemic-induced migration also shaped local housing dynamics, so we incorporate lagged yearly migration data, as well as lagged yearly migration data interacted with post, from the Statistics of Income through 2022. Finally, we add lagged monthly county-level COVID-19 infections from the Center for Disease Control. As reported in Table 6, while the inclusion of these controls has a slight diminishing effect on our magnitudes, mostly due to the exclusion of later years of our sample because of data availability, we find no effect on the significance of our results.

Beyond static controls, we compare dynamics directly. In Figure 3 we directly compare the dynamics of biodiversity exposure with those of other COVID-related housing demand measures. We use our continuous AUBI measure allowing us to include the full sample, and standardize each measure for direct comparison of coefficients, as well as including the full set of controls. We estimate dynamic treatment effects for range size rarity, work from home, and total park area. In all panels, we use a continuous measure of biodiversity exposure to alleviate concerns that our measure of COVID has a different cut off than our binary measure. In the first panel of figure 3 we compare the dynamic effects of range size rarity to the effect of protection weighted range size rarity. If there was a general shift in the the value of nature in 2020 due to COVID-19, then a more general value that captures all species should provide a larger and stronger effect. However, if the effect is driven instead by regulatory policy then only the unprotected portion of biodiversity should have an effect. Our figure demonstrates that the second hypothesis is correct. Range size rarity has almost no effect on house prices either before or after COVID-19, however the unprotected and regulatory exposed parts of nature have a much stronger and significant impact on house prices. In Panel B we compare the dynamic effect of work from home to our biodiversity exposure. The figure shows that house price effects linked to biodiversity sharply increase beginning in 2021 and persist through 2024, while the work from home dynamics remain essentially flat, in line with research suggesting that COVID's impact on housing markets peaked in 2020 and had largely dissipated by the second quarter of 2020 (Gupta et al. (2022)). The triple interaction addresses potential nonlinearities in how COVID might differentially affect high versus low exposure counties. We run several other tests with work from, for example, we also show the same dynamics at the

MSA level in figure IA.8 again showing no effect of COVID-19. Finally in panel C, we compare the dynamics of total park area in a county to the effects from total park area in a county as a further control against potential nature effects. Given that our effect does not follow trends similar to COVID effects, and that we construct controls that take account of possible correlation between our measure and COVID's effect implies that our previous regressions are distinct from COVID's effect.

Two additional pieces of evidence reinforce the distinction between COVID and biodiversity regulatory risk. First, COVID has been shown to significantly affect rent prices (Gupta et al. (2022)), yet we find no effect of biodiversity exposure on rents, consistent with a mechanism distinct from pandemic-driven shifts.[9]. Second, we document a reversal in housing price effects around the 2024 election of President Trump, when biodiversity policy expectations weakened.[10] Unless COVID shocks also shifted at that precise moment, this reversal provides independent confirmation that our results reflect policy-driven biodiversity risk rather than pandemic dynamics. Combined, our additional controls, dynamics, and independent confirmation tests using rents and the election of President Trump show that our effect is significantly distinct from any impact of COVID-19.

Another potential concern is that counties with high biodiversity exposure may also face elevated climate-related risks. Given that the election of President Biden was accompanied by heightened expectations of climate regulation, our results could partially reflect climate risk being priced into housing markets. As mentioned in the data section, we address the potential confounding effect of climate risk using a similar strategy. We include three controls for climate risk. First, we include NatureServe's Climate Exposure Score, measured for both near-term and mid-to-late-century projections. This score assesses the stress imposed by climate change and its projected impacts on ecosystems. The metric is based on two measures of climate vulnerability: Climate Departure and Climate Sensitivity. Climate Departure measures predicted climate change using

[9] Results for the effect on rents are reported in table IA.5

[10] Results for the effect of the election of President Trump are shown in figure 8. We discuss these results in more detail later in the paper.

multivariate approaches for 6 common temperature and precipitation variables between mid-20th-century averages and future 21st-century estimates. Climate Sensitivity measures the change in modeled suitability between the mid-20th century and future time periods based on Random Forest models constructed for the historic range of an ecosystem. For further details, see Comer et al. (2019). We then also include a further control for habitat climate change vulnerability. This metric combines climate exposure with the current climate resilience of an area to create a vulnerability score. Climate resilience is based on four primary indicators suitable for measuring relative sensitivity; landscape condition, invasive species, fire regime departure, and forest insect and disease risk. For further details, see Comer et al. (2019). These measures are plotted in Figure IA.2 and Figure IA.3. Including these controls has no meaningful effect on the significance or magnitude of our estimated coefficients, suggesting that climate risk is distinct from our measures of biodiversity exposure.

As a further test against potential bias from unobserved confounders, we implement the robustness analysis proposed by Oster (2019). The key intuition behind the test is that if including controls raises our R^2 by a large amount, but the coefficient remains stable there is less residual variance for unobservables to explain away our treatment effect and we can be confident in the magnitude and direction of our effect. The test from Oster (2019) formalizes this notion and returns a parameter, δ, that describes how much stronger the effect from unobservables would have to be relative to observables to drive our treatment effect to zero. For example, a δ of 1 means that the unobserved controls would need to be just as important as observed controls to explain away the treatment effect. The test requires one input, $R_{\max}$, which describes how much further including all controls would raise our R^2 by. Oster (2019) recommends setting the R^2 value to be 30% larger than the fully saturated model. At this level, we find a δ of 10.28. Thus, the effect from the unobserved component of COVID, parks, etc. would have to be 10 times as strong as the components we control for in order to drive our effect to 0. Figure IA.10 shows how our δ looks for a range of $R_{\max}$ estimates. In order for the unobserved component to be as important as our observed component, $\delta = 1$, including all unobserved variables would need to raise our R^2

by nearly six times, an implausibly large amount. Therefore, we are reasonably confident that our effect is not driven by omitted variable bias, including effects from COVID.

We also test whether the observed price effects are driven by the realization of conservation efforts or by expectations about future implementation. To evaluate these hypotheses, we use Zillow's Observed Rent Index (ZORI). By comparing rents, which adjust to clear the market in the short run, to house prices, which include a long-run component, we can test for whether our result is driven primarily by long-run expectations or short-run cash flow fluctuations. We implement the specification from Equation 2, substituting the outcome variable with the natural logarithm of Zillow's Observed Rent Index. Results are reported in Table IA.5. Results show that there is no effect on rent prices. As rent has less coverage, we also run a regression using our main house price variable but for the restricted sample. We continue to find a positive and significant effect on house prices in the restricted sample. These findings suggest that the effects of biodiversity regulatory risk on housing prices operate through long-term expectations rather than immediate changes. They also reinforce the interpretation that the price impact of biodiversity regulatory risk is driven by forward-looking expectations, rather than short-term realizations of regulatory action.

We conduct several further robustness checks to assess the sensitivity of our results. First, we show that our result is not sensitive to our choice of treatment. Figure IA.6 presents coefficient estimates from our main regression specification (Equation 2), varying the threshold used to define treatment status based on percentiles of county-level biodiversity exposure. In Panel A, we vary the treatment definition using the AUBI measure, comparing counties in the top $x\%$ of AUBI exposure to those in the bottom $1-x\%$, where x ranges from the 50th to 99th percentile. Panel B repeats this analysis using the PWRSR measure. Each point on the plot represents the estimated treatment effect for a given x, with 95% confidence intervals shown. All regressions include the full set of controls as well as county and state $\times$ year-month fixed effects. Standard errors are clustered at the county level. Across both panels, the estimated treatment effects remain statistically significant and positive across a wide range of thresholds. This pattern suggests that our primary results are not driven by an arbitrary cutoff, but instead reflect a relationship between biodiversity exposure and housing market outcomes. We conduct a similar exercise using the full sample. Figure IA.7 illustrates this robustness check, where we test alternative treatment thresholds while maintaining the full sample across specifications. For each threshold from the 50th to the 99th percentile, counties above the cutoff are classified as treated and those below as untreated, but the regression includes the full sample in all cases. As before, all regressions include the full set of controls, county and state $\times$ year-month fixed effects, and standard errors clustered at the county level. Panel A uses AUBI, and Panel B uses PWRSR. Each point reflects the estimated treatment effect on the log of house prices with 95% confidence intervals. Across both panels, the estimated effect size remains significant and positive across a wide range of cutoffs for treatment. These findings further support the claim that biodiversity exposure is systematically associated with housing market responses and that our results are not driven by arbitrary percentile cutoffs. Next, we turn to exploring heterogeneity within our sample.

5.3 House Prices and County's Reliance on Nature-Intensive Industries

In this section, we investigate whether the effect of biodiversity regulatory risk on house prices varies across counties with differing economic reliance on nature-based industries. Motivated by the findings that the companies most vulnerable to biodiversity-related regulation are those directly dependent on local ecological conditions (Pena et al. (2024)), we examine whether these economic exposures dampen the capitalization of regulatory risk into housing values. As discussed in the introduction, we hypothesize that potential government action that restricts land use in areas vital to industrial activity such as mining or oil extraction can lead to stranded assets and worse regional economic conditions, eventually depressing house prices.

In order to test this hypothesis, we construct a county-level measure of economic dependence on nature using data from the Quarterly Census of Employment and Wages (QCEW). The QCEW provides the total amount of wages earned in specific North American Industry Classification System (NAICS) industries within each county in each quarter. We take the total amount of wages earned in industries with two-digit NAICS codes equal to or less than 33. This includes industries such as agriculture, fishing, forestry, mining and oil and gas extraction, manufacturing, and other similar industries. We then take that sum and divide it by the total amount of wages in a county during the pre-period from 2017 to 2020. This measure captures the economic importance of nature-intensive activity prior to the shock. We plot the geographic distribution of our measure in Figure 4.

We then implement a triple difference-in-differences. We use as an outcome the natural log of the ZHVI. We use both our PWRSR and AUBI binary exposure variables. We interact exposure with a post-period dummy. This variable is then again interacted with a county's dependence on nature. We use both a continuous measure of wage share and a binary indicator. The indicator is equal to one for counties in the top tercile of wage share coming from nature-intensive industries and equal to zero for counties in the bottom tercile.

We implement the above design using the following specification:

$$\begin{aligned} ln(price)_{it} = \beta_0 + \beta_1(Treat \times Post)_{it} + \beta_2(Treat \times Post \times Economic\ Nature\ Intensity)_{it} \\ + \beta_3' X_{it} + \alpha_i + \delta_t + \gamma_{st} + \varepsilon_{it} \end{aligned} \tag{3}$$

The variable $(Treat \times Post \times Economic\ Nature\ Intensity)_{it}$ represents the triple interaction between treatment and the county's share of economic activity coming from resource dependent industries. Fixed effects and controls remain the same as in Equation 2.

Results are presented in Table 7. Columns (1) and (2) use our binary measure of exposure. Columns (3) and (4) use our continuous measure of exposure. In all columns, we find a negative effect of reliance on nature-intensive industries. For our preferred specification (column 2) we find a coefficient of -0.024. Thus, for a county in the bottom third of wage share in nature-reliant industries, we expect a 4.1% increase in house price. However, for counties with a similar level of biodiversity exposure but in the top tercile, we find that the effect attenuates to 1.7%. These results suggest that there is significant heterogeneity within our sample. Although we would expect counties that are exposed to see an appreciation in house prices on average, counties whose economies may be affected can see their housing wealth eroded by regulatory risk.

Panels A and B of Figure 5 present our dynamic analysis.[11] The figure plots both difference-in-differences and triple difference-in-differences coefficients. This allows us to visualize both pre-trends and the timing of the price response after the shock, as well as how the effects of nature-intensive industries evolve over time. We implement a dynamic version of Equation 3, retaining all variable definitions. We estimate four specifications: two using binary measures of county exposure to nature-dependent industries and two using a continuous measure, each measure then being interacted with our discrete versions of PWRSR or AUBI.

There are no significant differences in house price trends between treated and untreated counties prior to January 2021 or in counties that have a large reliance on nature-intensive industries. This supports the parallel trends assumption. Following the policy announcement, we observe a steady and statistically significant increase in house prices for treated counties relative to control counties and a similar decrease in the effect for counties that are heavily reliant on nature-intensive industries. Using Panel A, at the end of the sample period, when comparing counties in the bottom to the top tercile of biodiversity exposure we would expect a 6.1% increase in house values; however, for counties in the top tercile of reliance on nature-intensive industries, the effect is reduced by 3.5% resulting in an increase of only 2.4%.

6 Channels

In this section, we test several hypotheses regarding the mechanisms behind the observed average price effect. Given that we observe an increase in housing prices, there are two possible explanations. The price effect could stem from reduced supply of housing, increased demand for housing, or a combination of both.

To disentangle the underlying mechanism, we exploit heterogeneity in land characteristics across counties. Some areas will have a lower sensitivity to supply shocks than others, while simultaneously having a higher sensitivity to demand shocks. To capture this variation, we use

[11] We implement a triple difference in difference using a continuous measure of wage share in Figure IA.11

the land availability measure developed by Lutz and Sand (2023). This measure is constructed by taking the proportion of area in a county left after removing wetlands, water bodies and areas with a slope greater than 15%. Figure IA.12 presents the spatial distribution of land availability across counties. As land availability increases, we expect a monotonic decline in supply sensitivity and a corresponding rise in sensitivity to demand for nature. As noted in the data section, two alternative measures of supply elasticity are also commonly used in the literature. Baum-Snow and Han (2024) and Gyourko et al. (2008) both construct supply elasticity measures for a set of metropolitan areas. We do not use these alternative measures because they are limited to a small subset of urban areas. In contrast, the Lutz and Sand (2023) measure provides comprehensive coverage for all counties in the continental United States, making it more suitable for our analysis. Moreover, the alternative measures do not capture the opposing forces of constrained supply and rising demand for nature investments that our empirical strategy seeks to identify.

To validate the relationship between land availability and demand, we construct bin scatter plots showing the relationship between land availability and four nature-related measures: AUBI exposure, park area, wetland area, and nature deprivation. Nature deprivation is a measure constructed by the White House's environmental advisory body, the Council of Environmental Quality.[12] Bin scatters are shown in Figure 6. Each figure confirms a monotonic relationship between land availability and nature-related measures. As land availability increases, the supply channel is weakened, while at the same time the demand channel is strengthened. One further concern is that our results may be mechanical, that is, counties with greater land availability might be more likely to receive projects simply because more developable land exists. We show that this is not the case. In Panel E of Figure 6 we create another bin scatter and show that land availability has an inverse relationship with projects. This confirms that our main results are not mechanically driven by the availability of land or by the realization of government investment. We also present summary statistics for each land availability quartile in Table IA.6. The summary statistics confirm similar patterns to

[12]Nature deprivation is defined as "communities that disproportionately lack access to the climate mitigation and human health benefits of natural areas such as, but not limited to, parks, urban forests, conservation areas, open space and water-based recreation, public gardens, tree canopy cover, beaches, waterways, and other locally accessible green and blue spaces."

those observed in the bin scatters. Counties in the highest land availability quartile (Q4) receive the fewest projects and have the lowest AUBI scores and parks, while those in the lowest quartile receive the most projects and have the highest AUBI scores and park area.

Our first test examines whether the observed price effect is primarily driven by supply constraints or demand. We begin by dividing the land availability measure into quartiles. The spatial distribution of these quartiles is shown in Panel B of Figure IA.12. Quartile 1 contains counties with the least land availability and lowest nature deprivation, while Quartile 4 includes those with the most land availability and highest nature deprivation. We estimate Equation 2 separately within each quartile. Variable definitions remain the same as in Equation 2. We include all controls and fixed effects except for total park area. We do not include total park area in this specification, as we show land availability already captures the amount of nature available.[13]

Results are reported in Table 8. Perhaps surprisingly, we find that our results are concentrated in areas with higher elasticity. For the first and second quartiles, our estimates are borderline significant, while results for the fourth quartile are significant at the 1% level. Economically, we find that a one standard deviation increase in exposure in the first quartile leads to an increase in house prices of 0.5%. In contrast, we find that a one standard deviation increase in exposure in the fourth quartile leads to an increase of 2.1%.[14] These regressions imply that while a supply channel might be driving the effect, there also appears to be a significant demand channel as well.

Figure 7 presents our dynamic analysis conducted separately within each land availability quartile and using the continuous version of AUBI. In all panels of Figure 7, there are no significant

[13]Sub-setting by land availability controls for the park area so we do not include it in the regression. Nevertheless, we alternatively run all specifications with total park area as an additional control and find that it does not change our coefficients.

[14]As a robustness check, we re-estimate our main specification using the log of the AUBI measure as the exposure variable. Results are reported in Table IA.8. Results are qualitatively similar to our main results. We further test robustness using an alternative measure of land availability from Lutz and Sand (2023), referred to as "buildable land." This measure is constructed by removing developed areas and parks as well as wetlands, water and areas with a slope greater than 15% and dividing the remaining area by total area within counties. Results using this measure are presented in Table IA.9 and again align with our main findings. Throughout this section we use a continuous treatment. Recent critiques of continuous difference-and-differences has been raised by Callaway et al. (2024). To alleviate this concern and as a final test of robustness we implement Equation 2, but instead form treatment *within* each land availability quartile. This specification compares highly exposed counties to less exposed counties within the same quartile. Results are reported in Table IA.10, again show that the effects are concentrated in the fourth quartile of land availability.

differences in house price trends before January 2021, supporting the parallel trends assumption. Following the policy announcement, we observe a steady and statistically significant increase in house prices exclusively within the fourth quartile. As in our main specification, the price effect in the fourth quartile builds gradually and levels off toward the end of the sample period—consistent with delayed price adjustments in housing markets that exhibit search frictions and slow-moving responses (Case and Shiller (1988), Piazzesi and Schneider (2016)).[15] By contrast, the effect in other quartiles is much smaller. At the end of the sample period, the estimated coefficient for the fourth quartile reaches 0.44. This implies that, by the end of the sample period, a one standard deviation increase in exposure corresponds to a 2.2% increase in house value, or approximately $3,030 based on the median home value in the fourth quartile.

We also examine heterogeneity within land availability quartiles. We test our hypothesis that counties more reliant on nature-related industries will experience a muted effect in house prices from expected negative impacts on economic activity. Specifically, we implement Equation 3 but subset our sample by land availability quartiles. Results are reported in Table IA.11. We find a negative effect in both land availability quartiles one and two, but only find a significant effect in quartile four. This again suggests that while overall biodiversity regulatory risk has a positive impact on prices, this effect is reduced by the potential of economic damage caused by firm distress. Panel E of Figure 7 displays the dynamics of our triple interaction. Results are consistent with our main findings.

We next turn to exploring each of our channels in more detail. While biodiversity conservation may impose binding constraints in some areas, the absence of larger effects in more supply inelastic regions suggests that reductions in supply alone are unlikely to explain the observed price patterns. In less elastic areas, conservation efforts may be targeted toward already unbuildable land, limiting their impact on housing markets. In contrast, in more elastic areas, where develop-

[15] We also note that these dynamics show that our results are driven by expectations and not the realization of risk. The first projects and major Government action began towards the end of 2022. Looking at the dynamics for the fourth quartile we see that the price effect is mostly incorporated by the date of the first project. Furthermore, the fourth quartile received the fewest projects and had the largest price increase as well, further showing that our effects are not driven by general government action

ment was previously feasible, the introduction of new conservation easements or restrictions may be more salient, but supply constraints are still unlikely to bind immediately. This motivates a deeper exploration of the demand channel.

If the price effect also operates through the demand channel, a key condition is that the expected increase in natural investment associated with AUBI exposure is salient to homeowners. To assess salience, we measure media attention to projects and programs under the *30 by 30* initiative. We extract the number of article mentions at a monthly level from Factiva, as shown in Figure IA.13 using the method shown in Figure IA.14. The number of articles that reference the initiative increases sharply after the announcement of the executive order. This trend reflects heightened public attention to biodiversity conservation and associated government interventions, reinforcing the plausibility of demand side responses in housing markets.[16] We further test whether there could be a significant demand component using direct measures of demand. We use Google Mobility Reports data which provides the percent change in visits to particular categories of locations relative to a baseline period in 2019. We test our demand channel by focusing on changes in visits to park locations in the post-treatment period. We re-estimate Equation 2, using the county-level yearly average change in park visits relative to 2019 as the outcome variable. Results are presented in Table 9. We find that positive significant effects emerge only in the fourth quartile of land availability. Thus, while supply restrictions could play a role, it appears that a significant demand channel is operating as well.

6.1 Is Speculation Driving the Effect?

While both a supply decrease and demand increase can explain the direction of our effect, the magnitude of our coefficients suggests that additional mechanisms are at play. One such mechanism may be speculation, which could amplify the impact of conservation efforts. This possibility is important because biodiversity policy is likely to be subject to the same uncertainty as climate

[16] Table IA.12 provides excerpts from representative articles illustrating how conservation efforts were paired with the provision of public investments. Prior literature emphasizes that homeowners are acutely attentive to factors affecting property values, consistent with the notion that "everything is capitalized" in housing markets (Fischel (2002)).

policy. If speculation is a key driver of housing prices, then as biodiversity regulatory intensity waxes and wanes, speculative booms and busts may become a defining feature of highly exposed housing markets.

We implement three tests for speculation. Our first test follows the approach of Gao et al. (2020). Utilizing loan data from HMDA, we split loans based on the occupancy type - “primary residence”, “secondary residence”, and “investment.” Our test for speculation looks primarily at the effect on loans labeled as “investment." We first test if there is an increase in lending at all. Panels A Table 10 and Table 11 report the effect on the log of total value of loans applied for and originated. We find a statistically significant and positive effect only in the fourth quartile, confirming our hypothesis about the location of our effect. Panels B, C, and D of Table 10 then test which type of loan is being used to purchase homes by splitting our regression by loan type. We find that for loan applications, the only significant coefficient is for investment loans. We further examine which type of loans are getting more loan originations. We find that both primary residence and investment loans are significant (Panels B, C, and D of Table 11). This reinforces both our demand and speculation explanations. However, the magnitude for speculation is much larger and more significant, with a coefficient of 0.994 compared to 0.291. For example, for a one standard deviation increase in exposure for the fourth quartile (0.05) we would expect a 4.6% increase in investment loans compared to only a 1.4% increase in primary residence loans. Thus, while there seems to be an underlying increase in demand for housing by residents, this increase is being magnified by speculation.

Our second test for speculation compares land values to property values. As Nathanson and Zwick (2018) argues, speculation is easier in the land market than in the housing market. Therefore, our next test compares our effect on land values to property values. To do so, we use annual county-level land value and property value data compiled by Davis et al. (2021). They base their data on reported appraisal values. We re-estimate our main specification, replacing the outcome variable with the log of land value or with the log of property values. Regression results are reported in Panels A and B of Table 12. First, we note that we only find a significant effect for the fourth quartile, reinforcing our result from the previous section. We then compare the coefficients for the effect on property values to the effect on land values. For property values, we find a coefficient of 0.295. A one standard deviation increase in exposure leads to a 1.4% increase in property values. For land values, which are cheaper and easier for speculators to acquire, we find a coefficient of 0.402, or for a one standard deviation in exposure, an increase of 2.0%. Comparing the effect on property values to land values, we see that there is a greater increase in land values. Thus, we find evidence that speculation could be driving our main effect.[17]

For our final test, we follow Gao et al. (2020) and examine whether building permits respond to biodiversity regulatory risk. We use building permit data from the U.S. Census Building Permit Survey and regress the log number of approved permits for buildings, housing units, and the total value of permits on our measure of risk exposure. Because our measure captures anticipated rather than realized regulation, any observed response would reflect forward-looking behavior by speculators or developers. Results are reported in Panels A, B, and C of Table 13. We find a positive but statistically insignificant effect on building permits in Quartile 4.[18] While not definitive, this pattern is consistent with the idea that some developers or speculators may be accelerating construction in anticipation of future land-use restrictions. Taken together with our findings on investment loan activity and higher increases in land values compared to property values, these results suggest that speculative behavior contributes meaningfully to the observed price effects.

If this were a one time policy shock, speculative pressures on house prices would dissipate. However, if biodiversity policy sees reversals and restarts similar to climate policy, then repeated cycles of speculation could lead to booms and busts in highly exposed areas (Bolton and Kacperczyk (2021), Ilhan et al. (2021), Seltzer et al. (2022), Barnett (2024), Basaglia et al. (2025), Delis et al. (2019) Noailly et al. (2022)). The 2024 election of President Trump illustrates this dynamic; on his first day in office, he rescinded Executive Order 14008, terminating the 30×30 conserva-

[17] Davis et al. (2021) include two other measures of land and property values in their data. They include standardized versions of their measures which adjust for the fact that the price of land per acre tends to fall as acreage increases, the so-called "plattage effect". Results for standardized land values and standardized property values are reported in Table IA.20 and Table IA.21, respectively. For all outcomes, results are quantitatively similar to our reported main results.

[18] As a robustness check, we repeat the analysis using imputed permit values provided by the Census (Table IA.19). Results remain qualitatively unchanged.

tion initiative, while the freezing of IRA and BIL funding further weakened expectations of future conservation investment. To test for a reversal of our previously observed effects, we extend our dataset through March 2025 and re-estimate the dynamic difference-in-differences specification from Equation 2, this time using the month prior to the 2024 election as the reference period. Results of the dynamics are shown in Figure 8. Although the post-election window is short, we find that housing price effects in treated counties have begun to reverse. This suggests that housing markets will face recurring speculation as biodiversity policy becomes more or less important over time.

7 Conclusion

Governments have committed to protecting biodiversity, yet the impacts of this policy are unknown. In this paper, we estimate the impact that expected conservation efforts have on housing markets. We create a measure of exposure to regulatory interest using data from NatureServe constructed using machine learning. By exploiting the Biden administration's 30$\times$30 initiative as an exogenous shock to the probability that a county will receive some type of regulatory action, we are able to overcome significant endogeneity issues. Implementing a difference in differences design, we find that after the shock, a one standard deviation increase in exposure is associated with a 0.6% increase in house prices. However, these effects have significant heterogeneity. In areas heavily reliant on natural resources for their economy, effects are small or even negative.

Importantly, we show that while supply restrictions may play a role, the positive average effect is driven significantly by amenity demand and also by speculative dynamics, which amplify the capitalization of regulatory risk into prices. The role of speculation suggests that biodiversity policy may generate volatility in housing markets as regulatory intensity waxes and wanes. Taken together, our findings highlight a novel dimension of environmental risk in housing markets, underscore the policy trade-offs between conservation, economic growth, and housing affordability.

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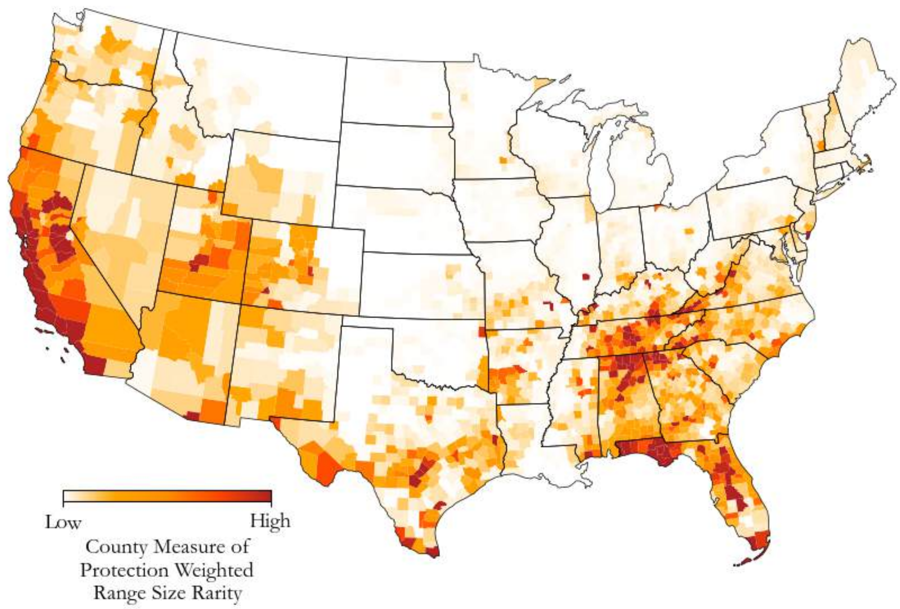
Figure 1: **County Level Biodiversity Regulatory Risk Exposure Measures**

This figure shows our measures of biodiversity regulatory risk that we adopted from NatureServe aggregated to the county level. Panel A shows county level Protection-weighted Range-size Rarity (PWRSR). Panel B shows Areas of Unprotected Biodiversity Importance (AUBIs). For each species, PWRSR is the product of two components: range-size rarity and the percentage of this habitat that lies outside protected areas. AUBIs are all map pixels with a summed PWRSR of 0.0005 or greater—a threshold set to identify areas with notable conservation importance. This PWRSR value of 0.0005 corresponds to a single species with a 500 km² range that is 25% unprotected, or a species with a smaller range of 20 km² that is 1% unprotected, or even multiple co-occurring species with lower individual PWRSR values. Protected areas are those classified with GAP Status 1 or 2 in the Protected Areas Database for the United States, which are areas mandated for biodiversity conservation.

Panel A: County Level PWRSR measure



Panel B: County Level AUBI measure

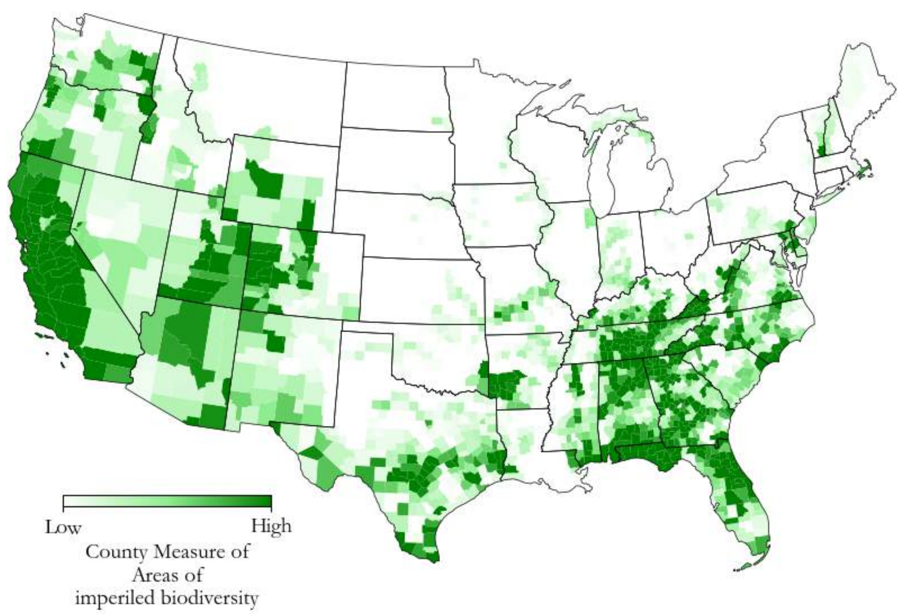
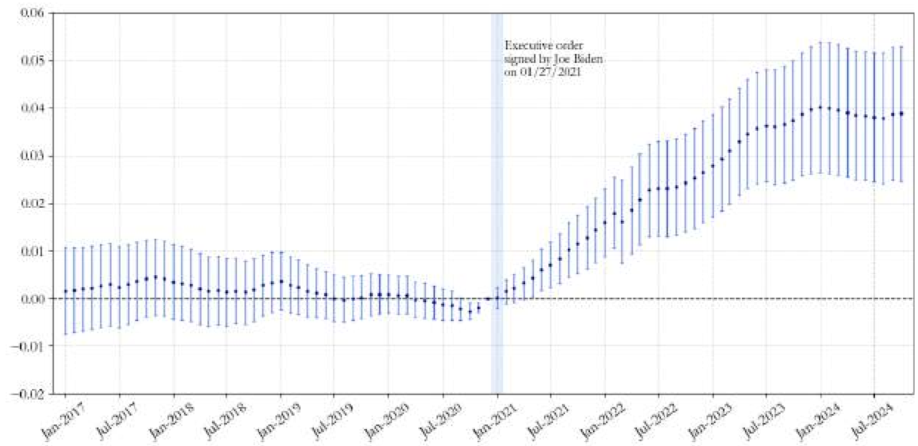
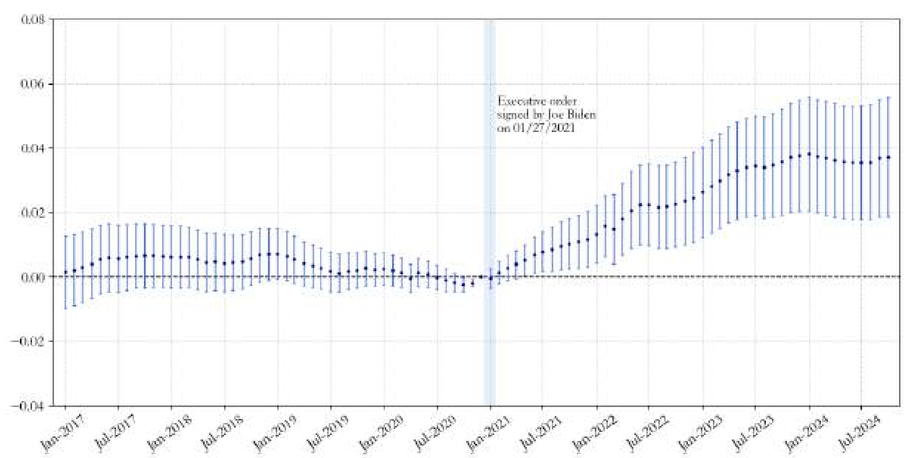


Figure 2: **Impact of Biodiversity Regulatory Risk on House Prices: Dynamics**

This figure tests the parallel trends assumption by plotting dynamic coefficients from a specification regressing the log of Zillow Home Value Index on indicators for top-tercile AUBI exposure. We implement a dynamic version of Equation 2. Panels A and B compare treated (top tercile) to control (bottom tercile) counties across two alternative biodiversity measures without including our triple interaction. We include the full set of controls and fixed effects for county and state $\times$ year-month. The vertical line indicates the signing of Executive Order 14008. Coefficients represent percent differences in home prices. Blue dots show point estimates for $Post \times Exposure$; vertical lines are 95% confidence intervals. Red dots show point estimates for $Post \times Exposure \times Economic\ Nature\ Intensity$. Standard errors are clustered at the county level. Panel A plots dynamic treatment effects using the AUBI biodiversity measure with December 2020 as the reference period. Panel B displays coefficients from the PWRSR biodiversity measure specification, also using December 2020 as the reference period.



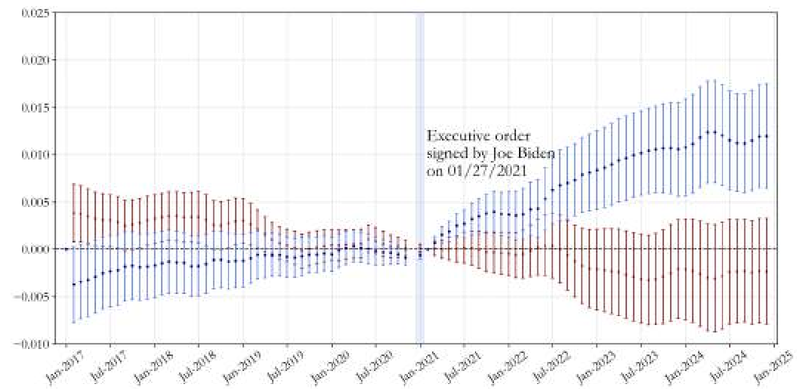
Panel A: AUBI Measure



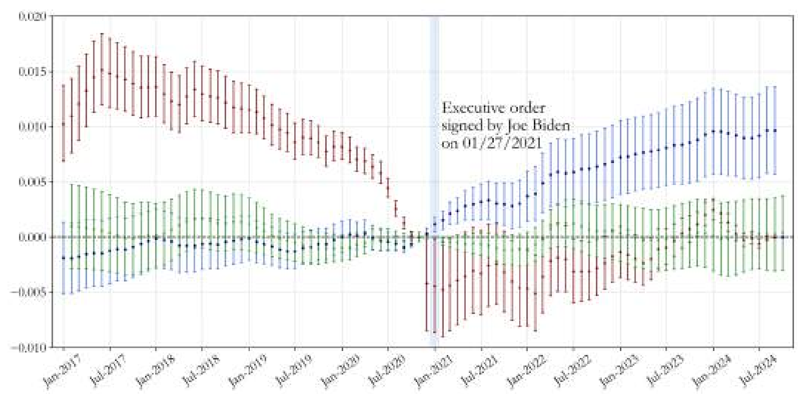
Panel B: PWRSR Measure

Figure 3: **Main Results Dynamics Compared with COVID Dynamics**

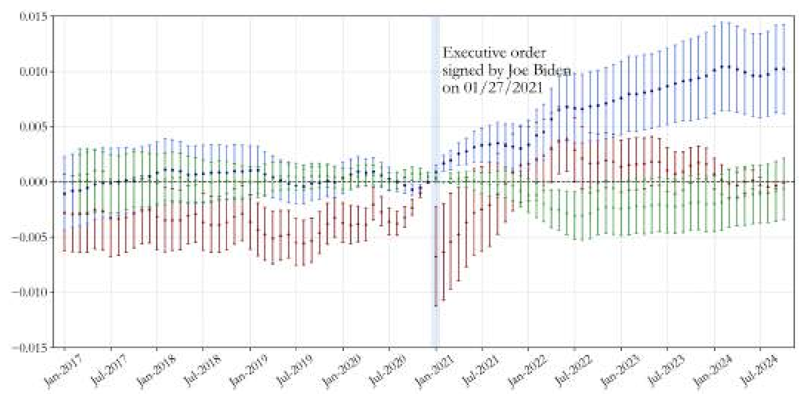
This figure tests the effects of standardized measures for COVID-19 and Biodiversity exposure in a dynamic setting. We implement a dynamic version of our main specification using continuous measure of exposure but have range size rarity, work from home share, and total park area treated as dynamic. Panel A compares all range size rarity in red to protection weighted range size rarity in blue. Panel B compares work from home in red to protection weighted range size rarity in blue, and a triple interaction in green. Panel C compares work from home in red to protection weighted range size rarity in blue, and a triple interaction in green. We include the full sample as well as the full set of controls and fixed effects for county and state × year-month. The vertical line indicates the signing of Executive Order 14008. Coefficients represent percent differences in home prices. Vertical lines are 95% confidence intervals. Blue dots show point estimates for $Post_t \times Exposure$ in all panels. Red dots show point estimates for $Post_t \times Range\ Size\ Rarity$ in Panel A, $Post_t \times Work\ From\ Home$ in Panel B, and $Post_t \times Total\ Park\ Area$ in Panel C. Green dots show point estimates for triple interactions. Standard errors are clustered at the county level.



Panel A: Range Size Rarity



Panel B: Work from Home

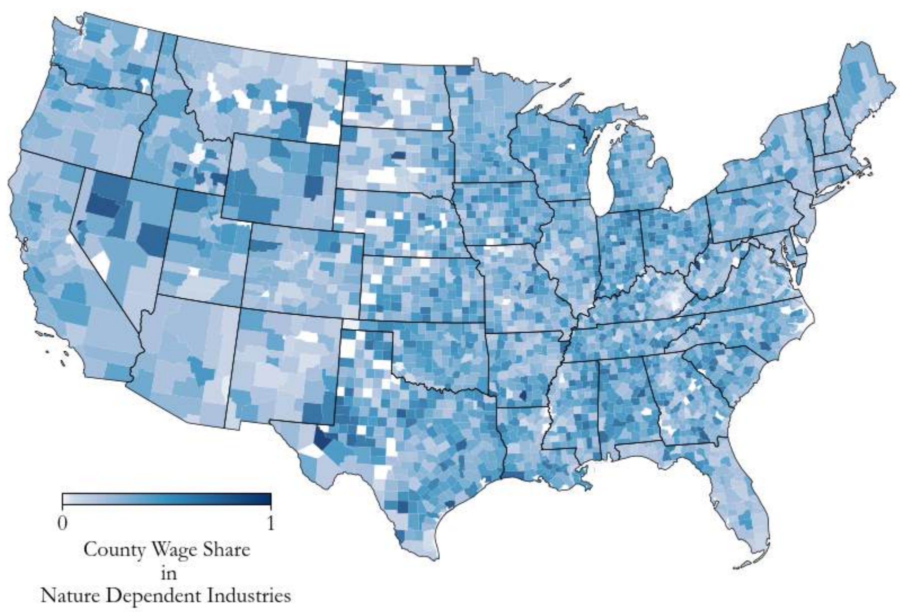


Panel C: Total Park Area

Figure 4: **County Wage Share From Nature and Location Dependent Industries**

This figure shows our measure of wage share coming from nature and location dependent industries. Panel A shows county level wage share from nature and location dependent industries. Panel B overlays our measure of AUBI with wage share from nature and location dependent industries. Wage share from nature and location dependent industries is calculated using the Quarterly Census of Employment and Wages. For a county, we sum the total amount of wages in a county coming from industries with two digit NAICS codes less than 33. This includes the following industries: Agriculture, Forestry, Fishing and Hunting, Mining, Quarrying, and Oil and Gas Extraction, Utilities, Construction, and Manufacturing. We take this sum and divide by the total wages earned in a county. We calculate a single value for each county using quarterly data from 2017-2020.

Panel A: Wage Share From Nature and Location Dependent Industries



Panel B: Wage Share From Nature and Location Dependent Industries with AUBI Measure

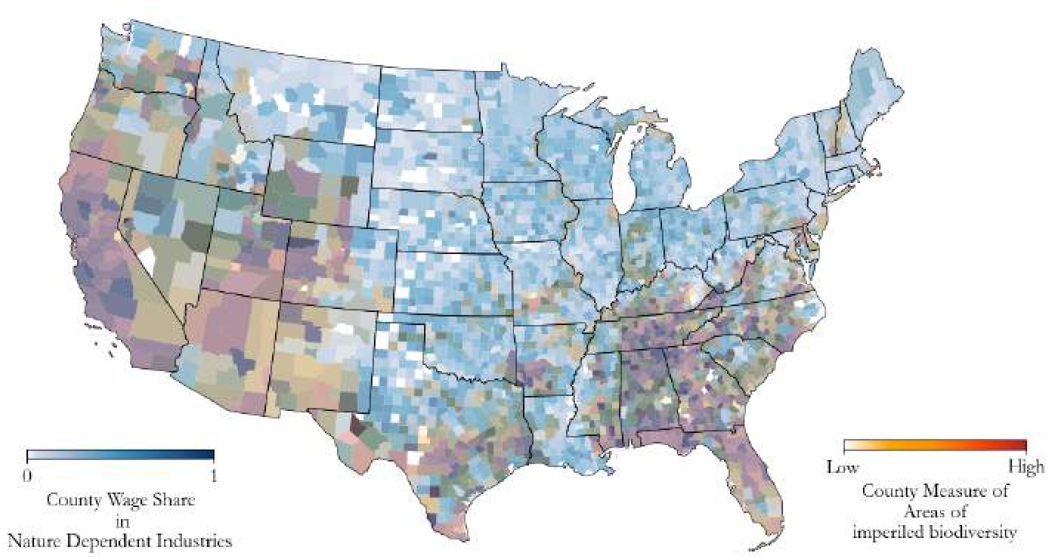
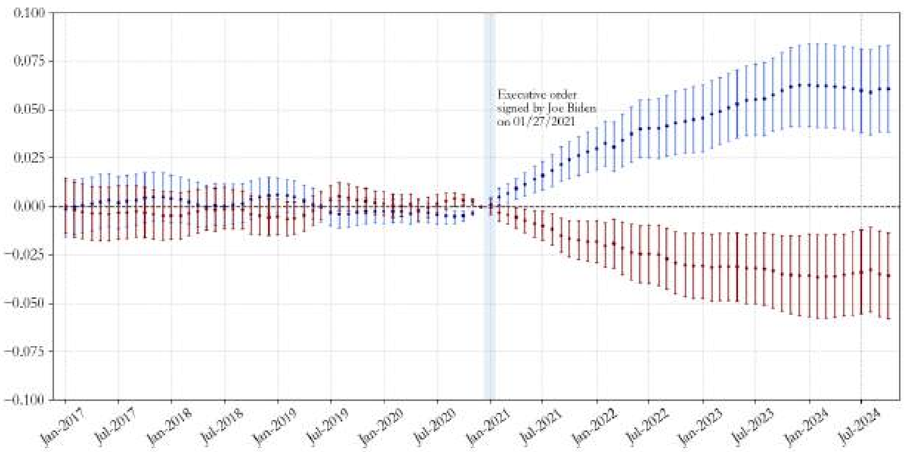
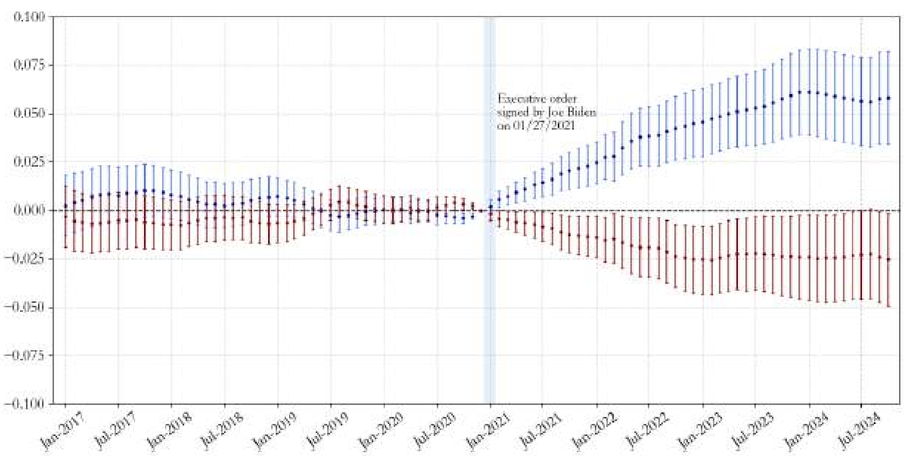


Figure 5: **Impact of Biodiversity Regulatory Risk on House Prices: Dynamics with Triple Difference for Reliance on Nature Intensive Industries**

This figure tests the parallel trends assumption by plotting dynamic coefficients from a specification regressing the log of Zillow Home Value Index on indicators for top-tercile AUBI exposure. We implement a dynamic version of Equation 2. Panels A and B compare treated (top tercile) to control (bottom tercile) counties across two alternative biodiversity measures including a triple interaction with either a binary indicator for being in the top tercile of wage share in nature intensive industries. We include the full set of controls and fixed effects for county and state $\times$ year-month. The vertical line indicates the signing of Executive Order 14008. Coefficients represent percent differences in home prices. Blue dots show point estimates for $Post \times Exposure$; vertical lines are 95% confidence intervals. Red dots show point estimates for $Post \times Exposure \times Economic\ Nature\ Intensity$. Standard errors are clustered at the county level. Panel A shows dynamic effects from the discrete AUBI measure with December 2020 as the reference period and includes our discrete measure of nature intensity. Panel B shows dynamic effects from the discrete PWRSR measure with December 2020 as the reference period and includes our discrete measure of nature intensity.



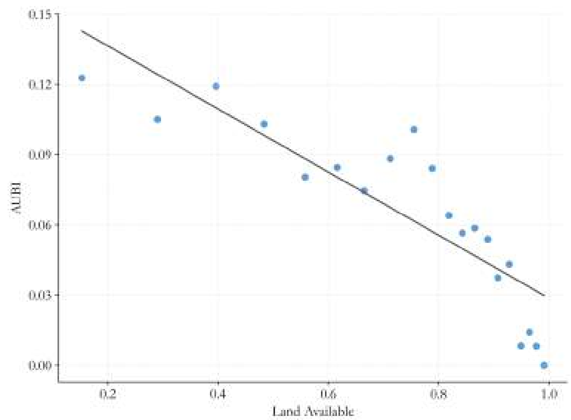
Panel A: AUBI Measure, Discrete Triple Difference



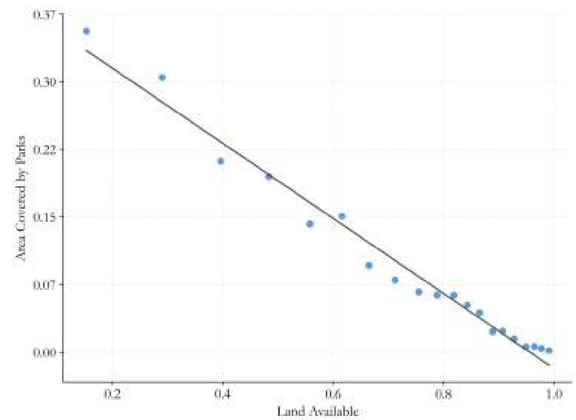
Panel B: PWRSR Measure, Discrete Triple Difference

Figure 6: **Relationships Between Land Availability and Nature Metrics**

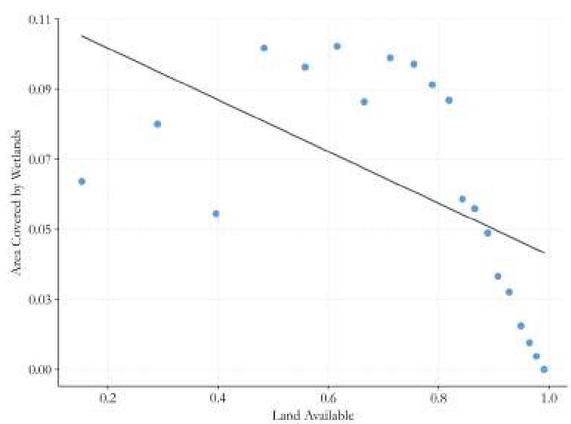
This figure shows the relationship between the Lutz and Sand (2023) measure of land availability and five key indicators of nature access and biodiversity. We bin the land availability measure and plot average values for each indicator within those bins. All panels display fitted linear trends. Panel (A) shows the relationship between land availability and AUBI (Areas of Unprotected Biodiversity). Panel (B) shows the relationship between land availability and the share of area covered by parks. Panel (C) examines the relationship between land availability and wetland coverage. Panel (D) examines the relationship between land availability and nature deprivation. Panel (E) examines the relationship between the number of projects started under the IRA and BIL and nature deprivation



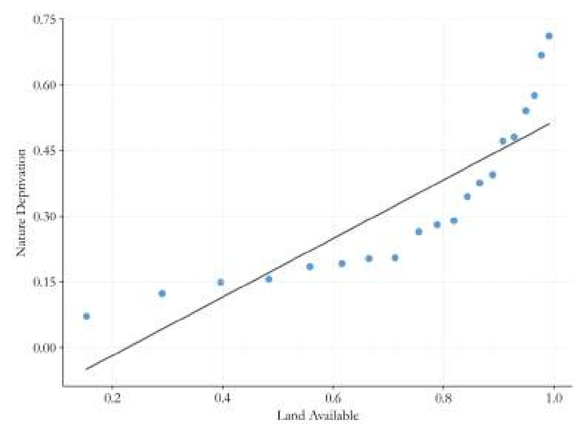
Panel A: AUBI



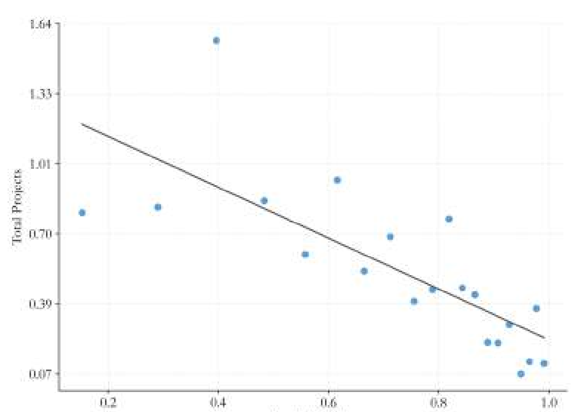
Panel B: Area Covered by Parks



Panel C: Area Covered by Wetlands



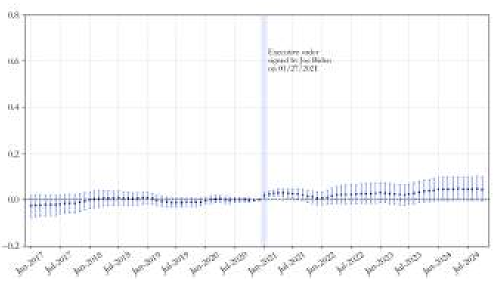
Panel D: Nature Deprivation



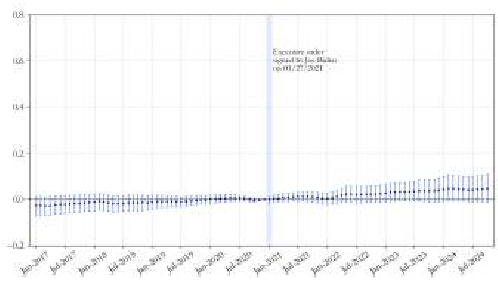
Panel E: Number of Projects

Figure 7: **Impact of Biodiversity Regulatory Risk on House Value Within Land Availability Quartiles: Dynamics**

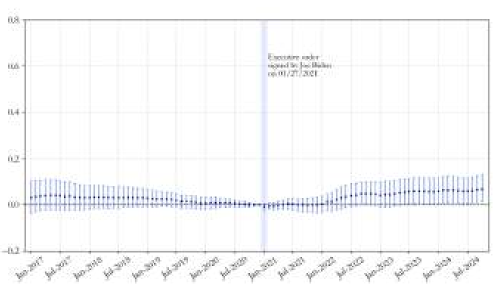
This figure tests the parallel trends assumption by plotting dynamic coefficients from a specification regressing the log of Zillow Home Value Index on our AUBI continuous measure of biodiversity exposure within Lutz and Sand (2023) land availability quartiles. We implement a dynamic version of Equation 2 and Equation 3, sub-setting to each land availability quartile. We include controls for Work From Home share, park area, climate risk (Habitat Climate Change Vulnerability Index, Climate Exposure Near Century, Climate Exposure Mid to Late Century), one month lagged log of employment, and fixed effects for county and state $\times$ year-month. The vertical line indicates the signing of Executive Order 14008. Coefficients represent percent differences in home prices. December 2020 is used as the reference period. Dots show point estimates; vertical lines are 95% confidence intervals. Standard errors are clustered at the county level. Panel A plots dynamic treatment effects for land availability quartile 1. Panel B plots dynamic treatment effects for land availability quartile 2. Panel C plots dynamic treatment effects for land availability quartile 3. Panel D plots dynamic treatment effects for land availability quartile 4. Panel E plots dynamic treatment effects for land availability quartile 4 as well as the triple interaction effect with wage share from nature intensive industries. All standard errors are clustered at the county level.



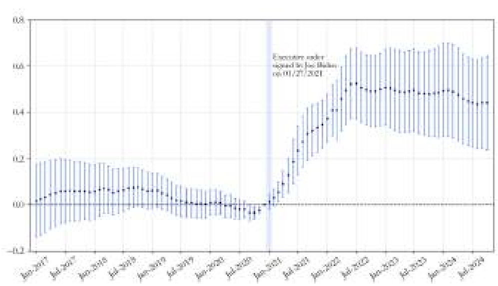
Panel A: Land Availability Quartile 1



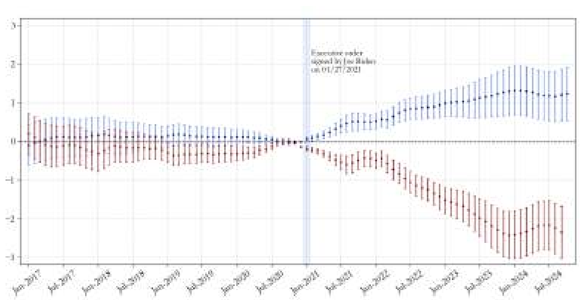
Panel B: Land Availability Quartile 2



Panel C: Land Availability Quartile 3



Panel D: Land Availability Quartile 4



Panel E: Land Availability Quartile 4 Triple Difference

Figure 8: **Effect of 2024 Election and Decrease in Biodiversity Regulatory Risk on House Prices in Fourth Land Availability Quartile**

This figure tests the effect of the President Trump's election and decrease in regulatory risk on house prices in the fourth Land Availability quartile. We implement Equation 2 but change our reference date to be October 2024, one month before the election of President Trump. The vertical lines signify the start of Trump's presidency and the rescinding of executive order 14008. The coefficient represents the percent difference in house prices. The dots indicate point estimates, and the vertical lines indicate 95% confidence intervals.

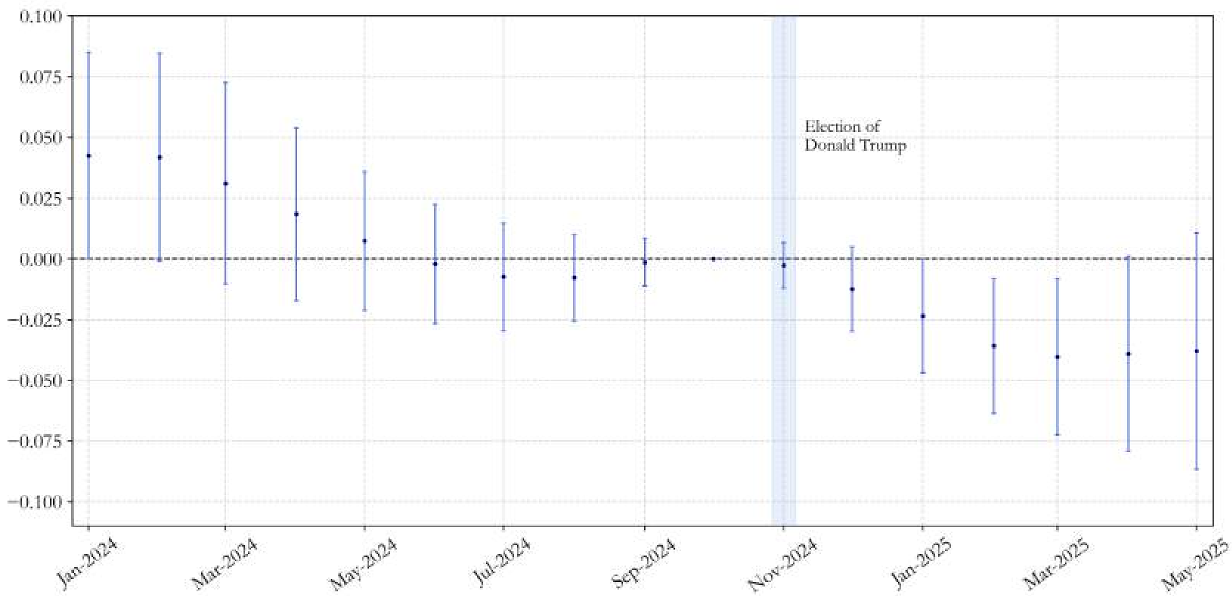


Table 1: **Summary Statistics**

This table presents the summary statistics for the variables used in the paper. Panels are separated by their source. The sample period is from Jan 2017 to Dec 2024.

	Level of Observation	Number of Observations	Mean	Std Dev	p5	p25	Median	p75	p95
Panel A: NatureServe									
Protection Weighted Range Size Rarity (PWRSR) (km^2)	County	3,055	2.07	4.69	0.00	0.10	0.41	1.80	9.92
Areas of Unprotected Biodiversity (AUBI)	County	3,055	0.07	0.13	0.00	0.00	0.00	0.07	0.34
Climate Exposure Near Century	County	2,747	0.72	0.14	0.47	0.64	0.73	0.82	0.93
Climate Exposure Mid Century	County	2,747	0.58	0.17	0.30	0.46	0.58	0.71	0.86
Habitat Climate Change Vulnerability Index Near Century	County	2,747	0.59	0.07	0.48	0.55	0.60	0.64	0.70
Habitat Climate Change Vulnerability Index Mid Century	County	2,747	0.53	0.09	0.39	0.47	0.52	0.59	0.67
Panel B: Zillow Data									
Zillow Home Value Index ('000)	County × Year-Month	297,412	204.28	146.13	78.89	120.25	164.95	239.89	451.04
Zillow Observed Rent Index	County × Year-Month	64,003	1,473.29	794.13	815.28	1,086.16	1,341.59	1,693.85	2,412.78
Panel C: Land Availability Data from Lutz and Sand (2023)									
Land Available (%)	County	3,055	0.73	0.24	0.23	0.59	0.81	0.92	0.98
Land Buildable (%)	County	1,995	0.60	0.28	0.04	0.40	0.66	0.85	0.93
Area Wetlands (%)	County	3,055	0.06	0.10	0.00	0.00	0.02	0.07	0.28
Panel D: TomTom & American Community Survey									
Total Park Area (%)	County	3,055	0.09	0.18	0.00	0.00	0.01	0.09	0.52
Work From Home	County	3,055	0.33	0.03	0.29	0.31	0.32	0.34	0.39
Panel E: Census TIGER									
County Land Area (km^2)	County	3,055	2,447	3,390	530	1,108	1,571	2,350	7,443
County Water Area (km^2)	County	3,055	139	547	1	7	19	57	631
Land Area Urban (%)	County	3,055	0.35	0.43	0.00	0.00	0.05	0.91	1.00
Panel F: Council on Environmental Quality									
Nature Deprived Score	County	3,055	0.33	0.30	0.02	0.08	0.22	0.56	0.92
Panel G: Housing Mortgage Disclosure Act									
Value of Loans Applied For ('000)	County × Year	16,024	573,907	1,977,204	7,670	28,635	82,965	316,560	2,639,485
Value of Loans Originated ('000)	County × Year	16,024	516,478	1,777,700	5,655	23,042	71,147	284,397	2,398,035
Value of Loans Applied for Investment ('000)	County × Year	16,024	33,988	158,627	185	1,000	3,305	14,452	145,105
Value of Loans Applied for Primary Residence ('000)	County × Year	16,024	510,659	1,757,387	6,485	25,280	70,772	274,142	2,418,000
Value of Loans Applied for Secondary Residence ('000)	County × Year	16,024	29,260	120,062	145	735	2,945	13,340	120,290
Value of Loans Originated for Investment ('000)	County × Year	16,024	30,217	139,613	145	865	2,995	13,022	130,055
Value of Loans Originated for Primary Residence ('000)	County × Year	16,024	459,722	1,583,772	4,645	19,770	60,010	243,777	2,182,400
Value of Loans Originated for Secondary Residence ('000)	County × Year	16,024	26,538	109,175	115	620	2,570	12,250	110,265
Panel H: Land Values Data From Davis et al. (2021)									
Property Values Standardized ('000)	County × Year	5,324	336	226	160	210	272	372	746
Land Value Appraisals ('000)	County × Year	5,324	318	980	36	65	116	234	1,053
Land Value Appraisals Standardized ('000)	County× Year	5,324	91	154	18	30	47	90	312
Property Values ('000)	County × Year	5,324	301	205	134	185	245	337	679
Land Value Share	County × Year	5,324	0.25	0.11	0.13	0.17	0.22	0.29	0.47
Panel I: Statistics of Income									
Net Migration	County × Year-Month	17,957	44.53	16,263.25	-5305	-309	179	1201	8484
Panel J: Centers for Disease Control									
Monthly New COVID cases	County × Year-Month	236,751	417	3,779	0	0	0	104	1,464
Panel K: Quarterly Census of Employment and Wages									
Employment ('000)	County × Year-Month	17,116	53.55	205.07	1.31	3.98	10.12	29.41	228.09
Wage Share from Nature-dependent Industries (%)	County	2,987	0.34	0.16	0.10	0.21	0.32	0.45	0.63
Panel L: Census Permit Survey Data									
Number of Building Permits Reported	County × Year	16,782	329.58	1,082.73	0	6	42	196	1,494
Number of Units Permits Reported	County × Year	16,782	520.71	1,923.75	0	6	49	244	2,349
Total Value of Permits Reported ('000)	County × Year	16,782	114,557.71	405,516.43	0.00	1,160.00	10,341.53	57,767.15	520,259.14
Number of Building Permits Imputed	County × Year	16,782	359.87	1,116.72	0	11	58	226	1,613
Number of Units Permits Imputed	County × Year	16,782	562.49	1,976.50	0	13	67	282	2,525
Total Value of Permits Imputed ('000)	County × Year	16,782	122,862.12	418,374.41	0.00	2,381.89	13,621.36	65,749.70	563,156.68
Panel M: Google Mobility Reports									
Change in Park Visits Relative to 2019 (%)	County × Year	3,013	13.56	40.81	-48.00	-16.68	8.48	40.76	85.26

Table 2: **Biodiversity Risk Exposure and County Characteristics**

This table examines the relationship between our measures of biodiversity risk and county level characteristics. The sample period is from 2017-2021. Columns (1) and (2) include climate risk variables (Habitat Climate Change Vulnerability Index,Climate Exposure Mid to Late Century, Climate Exposure Near Century) as well as geographic characteristics (Total Park Area, Percent Land Area Urban, Land Area, Water Area) and economic characteristics (Employment, GDP). Columns (3) and (4) include previous characteristics but also incorporates State fixed effects. Standard errors are clustered at the county level and reported in parenthesis. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

	Continuous PWRSR Exposure	Continuous AUBI Exposure	Continuous PWRSR Exposure	Continuous AUBI Exposure
	(1)	(2)	(3)	(4)
Habitat Climate Change Vulnerability Index	-1.563	0.054	5.060	0.153
	(4.662)	(0.115)	(4.914)	(0.113)
Climate Exposure Mid to Late Century	2.711	0.092	-0.514	-0.038
	(2.554)	(0.063)	(2.706)	(0.063)
Climate Exposure Near Century	0.042	-0.031	-1.623	-0.044
	(1.158)	(0.033)	(1.112)	(0.029)
Work From Home	-4.556	-0.149*	2.483	0.062
	(3.407)	(0.087)	(3.381)	(0.076)
Log(Employment)	0.286	0.029***	-0.008	0.009
	(0.387)	(0.008)	(0.284)	(0.006)
Total Park Area Percent	6.241***	0.151***	3.275***	0.072***
	(0.914)	(0.022)	(0.834)	(0.019)
Percent Urban Land Area	-0.840***	-0.020***	-0.208	-0.003
	(0.224)	(0.006)	(0.177)	(0.005)
Log(Land Area)	-0.381***	-0.010***	-0.895***	-0.016***
	(0.142)	(0.003)	(0.228)	(0.004)
Log(Water Area)	0.069	-0.003*	0.021	-0.002
	(0.077)	(0.002)	(0.061)	(0.002)
Log(GDP)	0.255	-0.015*	0.223	-0.003
	(0.414)	(0.008)	(0.277)	(0.006)
State FE:			✓	✓
R^2	0.086	0.083	0.416	0.444
Adj R^2	0.083	0.079	0.403	0.432
Within R^2	.086	.082	.039	.028
Obs	2,673	2,673	2,672	2,672

Table 3: **Biodiversity Regulatory Risk and Government Projects and Easments**

This table examines the relationship between unprotected biodiversity and government conservation projects started by the IRA and BIL as well as Easements started after 2021. We use county level values of biodiversity risk. The first two rows regress our outcome variables on a binary variable equal to 1 if a county's biodiversity risk exposure is in the top tercile and equal to 0 if it is in the bottom tercile. The next two rows use a continuous measure of exposure for all counties. Each column represents a different outcome. In panel A we investigate projects started under the IRA and BIL. "Has project" is a binary variable on whether a grid has a project centroid within its geography, in this table we report the percent value. "# of projects" is a continuous measure of the number of project centroids within grid. "Has Funding" is a binary variable equal to 1 if a project has been allocated a funding amount and 0 otherwise. "Amount Funded" is a continuous measure of the amount allocated to a project. If a project is not funded, its amount is replaced as 0. In panel B we investigate the relationship between regulatory risk and easements. An easement is considered conservation if its purpose is labeled as environmental, recreation, or scenic. "Has project" is a binary variable equal to 1 if a county has an intersecting geometry with an easement. "# of projects" is a discrete measure of the number of easement geometries that intersect a county. "Has conservation project" is a binary variable equal to 1 if a county has an intersecting geometry with a conservation easement. "# of conservation" projects is a discrete measure of the number of conservation easement geometries that intersect a county. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Panel A: Government Projects				
	Has Project (%)	# of Projects	Has Funding (%)	Amount Funded
Mean of Outcome Variable	24.17	0.697	10.24	1,680,508.99
Top Tercile Areas of Unprotected Biodiversity Importance	7.588***	0.435***	1.302	1,923,217.06*
	(0.159)	(0.011)	(0.113)	(75,863.63)
Top Tercile Protected Weighted Range Size Rarity	8.101***	0.469***	1.910	2,409,059.03**
	(0.159)	(0.011)	(0.113)	(75,839.40)
Areas of Unprotected Biodiversity Importance	3.894***	0.227***	1.770*	1,226,295.29***
	(0.076)	(0.005)	(0.054)	(284,759.86)
Protection Weighted Range Size Rarity	5.173***	0.299***	3.151***	1,415,654.87**
	(0.810)	(0.072)	(0.788)	(696,922.54)

Panel B: Easements				
	Has Easement (%)	# of Easement	Has Conservation Easement	# of Conservation Easement
Mean of Outcome Variable	17.809	1.023	4.715	0.093
Top Tercile Areas of Unprotected Biodiversity Importance	10.611***	0.356*	4.289***	0.098***
	(1.552)	(0.210)	(0.910)	(0.026)
Top Tercile Protected Weighted Range Size Rarity	10.351***	0.390*	4.889***	0.111***
	(1.551)	(0.212)	(0.922)	(0.026)
Areas of Unprotected Biodiversity Importance	5.084***	0.201**	1.615***	0.033***
	(0.826)	(0.080)	(0.449)	(0.012)
Protection Weighted Range Size Rarity	3.667***	0.196**	0.599**	0.021*
	(0.794)	(0.088)	(0.306)	(0.013)

Table 4: **Impact of Biodiversity Regulatory Risk on House Value**

This table examines the relationship between home value in counties that are in the top tercile of exposure to biodiversity regulatory risk to the home value in counties that are in the bottom tercile of exposure to biodiversity regulatory risk (Equation 2). The sample period is from 2017 to 2024. The outcome variable is the log of Zillow Home Value Index. Columns (1),(3),(5) use Protection Weighted range-size rarity as our measure of risk. Columns (2), (4), (6) use our Area of Unprotected Biodiversity Importance to measure biodiversity regulatory risk. We create a binary measure equal to 1 if a county is in the top tercile of exposure and equal to 0 if a county is in the bottom tercile of exposure. Columns (1) and (2) focus solely on the difference-in-differences estimates. Columns (3) and (4) incorporate controls for Work From Home and Total Park Area, our climate exposure measures, as well as county and year-month fixed effects. Columns (5) and (6) present the full model, which includes all explanatory variables as well as county, month, and state × year-month fixed effects. Standard errors are clustered at the county level and reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Top Tercile Protected Weighted Range Size Rarity × Post	0.061***		0.050***		0.020***	
	(0.006)		(0.005)		(0.007)	
Top Tercile Areas of Unprotected Biodiversity Importance × Post		0.061***		0.045***		0.023***
		(0.005)		(0.004)		(0.005)
Top Tercile Protected Weighted Range Size Rarity	0.257***					
	(0.022)					
Top Tercile Areas of Unprotected Biodiversity Importance		0.177***				
		(0.022)				
Post	0.289***	0.292***				
	(0.004)	(0.004)				
Post × Work From Home			-0.450***	-0.374***	-0.248***	-0.247***
			(0.072)	(0.060)	(0.064)	(0.060)
Post × Total Park Area (%)			0.088***	0.065***	0.064***	0.043***
			(0.015)	(0.015)	(0.011)	(0.011)
Post × Climate Exposure Near Century			-0.347***	-0.357***	-0.030	-0.039
			(0.059)	(0.054)	(0.053)	(0.048)
Post × Climate Exposure Mid to Late Century			0.070***	0.094***	0.057**	0.051**
			(0.024)	(0.023)	(0.023)	(0.020)
Post × Habitat Climate Change Vulnerability Index			0.358***	0.344***	-0.108	-0.065
			(0.094)	(0.092)	(0.096)	(0.085)
Log(Employment)			0.208***	0.210***	0.125***	0.122***
			(0.021)	(0.019)	(0.018)	(0.015)
Adj R-squared	0.160	0.128	0.986	0.986	0.992	0.992
Obs	170,584	194,660	170,584	194,660	170,584	194,660
County FE			✓	✓	✓	✓
Month FE			✓	✓	✓	✓
State X Year-Month FE					✓	✓

Table 5: **Impact of Biodiversity Regulatory Risk on House Value Using Continuous Measures**

This table examines the relationship between counties' exposure to biodiversity regulatory risk and home value (Equation 2). The sample period is from 2017 to 2024. The outcome variable is the log of Zillow Home Value Index. Columns (1), (3), and (5) use Protection Weighted range-size rarity as our measure of risk. Columns (2), (4), and (6) use our Area of Unprotected Biodiversity Importance to measure biodiversity regulatory risk. We use a continuous measure of biodiversity regulatory risk in all columns. Columns (1) and (2) focus solely on the difference-in-differences estimates. Columns (3) and (4) incorporate controls for Work From Home and Total Park Area, our climate exposure measures, as well as county and month fixed effects. Columns (5) and (6) present the full model, which includes all explanatory variables as well as county, month, and state × year-month fixed effects. Columns (7) and (8) present the full model, but using the log of our continuous measure for our measure of exposure to biodiversity regulatory risk. Standard errors are clustered at the county level and reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Zillow Home Value Index)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Protection Weighted Range Size Rarity × Post	32.736***		18.313***		4.237			
	(6.146)		(4.618)		(3.351)			
Areas of Unprotected Biodiversity Importance × Post		0.186***		0.127***		0.047***		
		(0.016)		(0.014)		(0.012)		
Log(Protection Weighted Range Size Rarity) × Post							0.005***	
							(0.001)	
Log(Areas of Unprotected Biodiversity Importance) × Post								0.003*
								(0.001)
Protection Weighted Range Size Rarity	236.737***							
	(27.711)							
Areas of Unprotected Biodiversity Importance		0.756***						
		(0.094)						
Post	0.310***	0.304***						
	(0.003)	(0.003)						
Post × Work From Home			-0.336***	-0.336***	-0.209***	-0.215***	-0.244***	-0.108*
			(0.057)	(0.057)	(0.051)	(0.051)	(0.051)	(0.061)
Post × Total Park Area (%)			0.109***	0.103***	0.056***	0.054***	0.047***	0.054***
			(0.013)	(0.013)	(0.010)	(0.010)	(0.010)	(0.012)
Post × Climate Exposure Near Century			-0.336***	-0.324***	-0.070	-0.066	-0.082*	-0.105
			(0.051)	(0.051)	(0.045)	(0.044)	(0.045)	(0.067)
Post × Climate Exposure Mid to Late Century			0.077***	0.066***	0.036**	0.035*	0.038**	0.057**
			(0.020)	(0.021)	(0.018)	(0.018)	(0.018)	(0.026)
Post × Habitat Climate Change Vulnerability Index			0.335***	0.321***	0.002	-0.003	0.026	0.000
			(0.080)	(0.080)	(0.074)	(0.074)	(0.075)	(0.113)
Log(Employment)			0.225***	0.217***	0.122***	0.121***	0.124***	0.119***
			(0.019)	(0.018)	(0.015)	(0.015)	(0.014)	(0.018)
Adj R^2	0.143	0.132	0.985	0.985	0.991	0.991	0.991	0.992
Obs	253,707	253,707	253,707	253,707	253,707	253,707	251,660	148,877
County FE			✓	✓	✓	✓	✓	✓
Month FE			✓	✓	✓	✓	✓	✓
State X Year-Month FE					✓	✓	✓	✓

Table 6: **Impact of Biodiversity Regulatory Risk on House Value with Additional Controls for COVID-19**

This table examines the relationship between counties' exposure to biodiversity regulatory risk and home value (Equation 2) with additional controls for effects from COVID-19. We include lagged per capita yearly net migration from the statistics of income as well as lagged monthly COVID infections from the CDC. The sample period is from 2017 to 2022. The outcome variable is the log of Zillow Home Value Index. Columns (1) and (2) use our binary measure of exposure while Columns (3) and (4) use our continuous measures. All columns include county, month, and state × year-month fixed effects. Standard errors are clustered at the county level and reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Zillow Home Value Index)			
	(1)	(2)	(3)	(4)
Top Tercile Protection Weighted Range Size Rarity × Post	0.011**			
	(0.005)			
Top Tercile Areas of Unprotected Biodiversity Importance × Post		0.014***		
		(0.004)		
Protection Weighted Range Size Rarity × Post			2.181	
			(2.794)	
Areas of Unprotected Biodiversity Importance × Post				0.037***
				(0.011)
Log(Monthly COVID Infections)	-0.001**	-0.001*	-0.001**	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Net Migration Per Capita	-0.038***	-0.037***	-0.038***	-0.038***
	(0.009)	(0.009)	(0.009)	(0.009)
Post × Net Migration Per Capita	0.313***	0.308***	0.318***	0.312***
	(0.028)	(0.027)	(0.028)	(0.027)
Post × Work From Home	-0.217***	-0.229***	-0.211***	-0.236***
	(0.052)	(0.051)	(0.052)	(0.050)
Post × Total Park Area (%)	0.047***	0.030***	0.048***	0.030***
	(0.010)	(0.009)	(0.010)	(0.009)
Post × Climate Exposure Near Century	-0.010	-0.019	-0.012	-0.019
	(0.045)	(0.041)	(0.045)	(0.041)
Post × Climate Exposure Mid–Late Century	0.045**	0.042**	0.045**	0.037**
	(0.020)	(0.017)	(0.019)	(0.017)
Post × HCCVI	-0.117	-0.085	-0.118	-0.080
	(0.081)	(0.073)	(0.080)	(0.072)
Log(Employment)	0.076***	0.072***	0.077***	0.073***
	(0.014)	(0.013)	(0.014)	(0.013)
Adj R^2	0.994	0.994	0.994	0.994
Obs	141,821	162,104	141,821	162,104
County FE	✓	✓	✓	✓
Month FE	✓	✓	✓	✓
State X Year-Month FE	✓	✓	✓	✓

Table 7: **Impact of Biodiversity Regulatory Risk on House Value and Nature Intensive Industries**

This table examines the relationship between home value in counties that are in the top tercile of exposure to biodiversity regulatory risk to the home value in counties that are in the bottom tercile of exposure to biodiversity regulatory risk as well as the proportion of wages in nature intensive industries. (Equation 3). The sample period is from 2017 to 2024. The outcome variable is the log of Zillow Home Value Index. Columns (1),(3) use Protection Weighted range-size rarity as our measure of risk. Columns (2),(4) use our Area of Unprotected Biodiversity Importance to measure biodiversity regulatory risk. We create a binary measure equal to 1 if a county is in the top tercile of exposure and equal to 0 if a county is in the bottom tercile of exposure. Columns (1) and (2) use a binary measure of dependence on nature. Columns (3) and (4) use our continuous measure. Columns include all controls as well as county, month, and state × year-month fixed effects. Standard errors are clustered at the county level and reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Top Tercile Protected Weighted Range Size Rarity × Post	0.029***		0.031***	
	(0.011)		(0.011)	
Top Tercile Areas of Unprotected Biodiversity Importance × Post		0.041***		0.043***
		(0.008)		(0.009)
Top Tercile Protected Weighted Range Size Rarity × Post × Top Tercile Wage Share from Nature-dependent Industries	-0.016			
	(0.010)			
Top Tercile Areas of Unprotected Biodiversity Importance × Post × Top Tercile Wage Share from Nature-dependent Industries		-0.024***		
		(0.009)		
Top Tercile Protected Weighted Range Size Rarity × Post × Wage Share from Nature-dependent Industries			-0.037	
			(0.025)	
Top Tercile Areas of Unprotected Biodiversity Importance × Post × Wage Share from Nature-dependent Industries				-0.061***
				(0.022)
Post × Top Tercile Wage Share from Nature-dependent Industries	0.005	0.010		
	(0.008)	(0.007)		
Post × Wage Share from Nature-dependent Industries			-0.005	0.010
			(0.020)	(0.017)
Post × Work From Home	-0.305***	-0.285***	-0.295***	-0.280***
	(0.083)	(0.081)	(0.066)	(0.064)
Post × Total Park Area (%)	0.060***	0.042***	0.059***	0.038***
	(0.014)	(0.012)	(0.011)	(0.011)
Post × Climate Exposure Near Century	-0.113	-0.096	-0.033	-0.042
	(0.076)	(0.067)	(0.054)	(0.048)
Post × Climate Exposure Mid to Late Century	0.082***	0.060**	0.056**	0.048**
	(0.032)	(0.028)	(0.023)	(0.020)
Post × Habitat Climate Change Vulnerability Index	-0.035	-0.009	-0.098	-0.051
	(0.141)	(0.131)	(0.098)	(0.087)
Log(Employment)	0.117***	0.113***	0.128***	0.129***
	(0.023)	(0.019)	(0.019)	(0.016)
Adj. R-squared	0.991	0.991	0.992	0.992
Obs	111,187	127,144	166,361	190,205
County FEs	✓	✓	✓	✓
State × Year-Month FEs	✓	✓	✓	✓

Table 8: **Impact of Biodiversity Regulatory Risk on House Value Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and the log of Zillow Home Price Index within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). The sample period is from 2017 to 2024. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 includes counties with the least land available for building, while Quartile 4 includes those with the most. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Zillow Home Price Index)			
	(1) Land Availability Quartile 1	(2) Land Availability Quartile 2	(3) Land Availability Quartile 3	(4) Land Availability Quartile 4
Post × Areas of Unprotected Biodiversity Importance	0.036*	0.037*	0.012	0.371***
	(0.020)	(0.019)	(0.028)	(0.078)
Log(Employment)	0.085***	0.092***	0.105***	0.124***
	(0.015)	(0.025)	(0.031)	(0.036)
Post × Work From Home	-0.329***	-0.274***	-0.323***	-0.161
	(0.113)	(0.106)	(0.099)	(0.104)
Post × Climate Exposure Near Century	-0.148**	-0.361***	-0.015	0.245**
	(0.065)	(0.133)	(0.121)	(0.117)
Post × Climate Exposure Mid to Late Century	0.020	0.117***	0.064	0.103*
	(0.029)	(0.043)	(0.045)	(0.058)
Post × Habitat Climate Change Vulnerability Index	0.188*	0.311	-0.189	-0.414**
	(0.100)	(0.261)	(0.224)	(0.205)
Adj. R-squared	0.995	0.990	0.987	0.987
Obs.	52,384	65,172	67,194	68,111
County FEs	✓	✓	✓	✓
State × Year-Month FEs	✓	✓	✓	✓

Table 9: **Impact of Biodiversity Regulatory Risk on Park Visits Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and park visits from Google Mobility data within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). Google Mobility data are created with aggregated, anonymized sets of data from users who have turned on the Location History setting. The sample period is from 2020 to 2022. Mobility reports are at the county × year level and the change is referenced to a baseline in 2019. Parks categories is defined as "places like local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens." We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 includes counties with the least land available for building, while Quartile 4 includes those with the most. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Yearly Average Change in Park Visits (%)			
	(1) Land Availability Quartile 1	(2) Land Availability Quartile 2	(3) Land Availability Quartile 3	(4) Land Availability Quartile 4
Post × Areas of Unprotected Biodiversity Importance	5.724	10.856	-8.608	36.070**
	(6.364)	(7.129)	(7.228)	(15.380)
Log(Employment)	-17.967	-2.401	28.575	-15.078
	(26.849)	(26.475)	(24.480)	(30.292)
Post × Work From Home	-98.945***	-13.433	-29.343	-36.068
	(24.663)	(20.594)	(28.296)	(34.879)
Post × Climate Exposure Near Century	-24.960	-63.727	-13.925	-63.643
	(21.171)	(45.025)	(49.253)	(69.208)
Post × Climate Exposure Mid to Late Century	24.997***	-14.113	3.887	-24.586
	(8.685)	(9.493)	(10.158)	(20.566)
Post × Habitat Climate Change Vulnerability Index	25.108	152.014	40.208	231.217
	(28.953)	(96.243)	(91.064)	(145.845)
Adj. R-squared	0.944	0.953	0.951	0.949
Obs.	851	672	648	369
County FEs	✓	✓	✓	✓
State × Year FEs	✓	✓	✓	✓

Table 10: **Impact of Biodiversity Regulatory Risk on Loan Applications Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and the sum of HMDA mortgages applied for in a county overall and by purpose within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). HMDA loans are at the county $\times$ year level. Investment loans are loans in which occupancy type is reported as investment. Primary residence loans are loans in which occupancy type is reported as "primary residence." Secondary residence loans are loans in which occupancy type is reported as "secondary residence." The sample period is from 2017 to 2023. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 has the least land available for building while Quartile 4 has the most land available for building. All regressions are run using our full set of controls and county as well as state $\times$ year fixed effects. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Land Availability Quartile 1	Land Availability Quartile 2	Land Availability Quartile 3	Land Availability Quartile 4
Panel A: All Loans, Log(Loan Amount Applied For)				
Post $\times$ Areas of Unprotected Biodiversity Importance	0.022	-0.063	0.046	0.288**
	(0.051)	(0.040)	(0.055)	(0.131)
Obs.	3,264	3,891	3,738	3,277
Panel B: Investment Loans, Log(Loan Amount Applied For)				
Post $\times$ Areas of Unprotected Biodiversity Importance	0.083	0.315**	0.220	0.929**
	(0.145)	(0.136)	(0.154)	(0.407)
Obs.	3,264	3,891	3,738	3,277
Panel C: Primary Residence Loans, Log(Loan Amount Applied For)				
Post $\times$ Areas of Unprotected Biodiversity Importance	0.008	-0.101**	0.012	0.218
	(0.048)	(0.040)	(0.059)	(0.141)
Obs.	3,264	3,891	3,738	3,277
Panel D: Secondary Residence Loans, Log(Loan Amount Applied For)				
Post $\times$ Areas of Unprotected Biodiversity Importance	-0.091	-0.037	-0.059	-0.028
	(0.104)	(0.136)	(0.246)	(0.454)
Obs.	3,264	3,891	3,738	3,277
For All Panels				
Controls	✓	✓	✓	✓
County FEs	✓	✓	✓	✓
State $\times$ Year FEs	✓	✓	✓	✓

Table 11: **Impact of Biodiversity Regulatory Risk on Loan Origination Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and the sum of HMDA mortgages originated in a county overall and by purpose within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). HMDA loans are at the county $\times$ year level. Investment loans are loans in which occupancy type is reported as investment. Primary residence loans are loans in which occupancy type is reported as "primary residence." Secondary residence loans are loans in which occupancy type is reported as "secondary residence." The sample period is from 2017 to 2023. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 has the least land available for building while Quartile 4 has the most land available for building. All regressions are run using our full set of controls and county as well as state $\times$ year fixed effects. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Land Availability Quartile 1	Land Availability Quartile 2	Land Availability Quartile 3	Land Availability Quartile 4
Panel A: All Loans, Log(Loan Amount Originated)				
Post $\times$ Areas of Unprotected Biodiversity Importance	0.021	-0.063	0.040	0.370***
	(0.055)	(0.042)	(0.059)	(0.142)
Obs.	3,264	3,891	3,738	3,277
Panel B: Investment Loans, Log(Loan Amount Originated)				
Post $\times$ Areas of Unprotected Biodiversity Importance	0.124	0.416***	0.218	0.994**
	(0.151)	(0.151)	(0.167)	(0.422)
Obs.	3,264	3,891	3,738	3,277
Panel C: Primary Residence Loans, Log(Loan Amount Originated)				
Post $\times$ Areas of Unprotected Biodiversity Importance	-0.000	-0.105**	0.007	0.291*
	(0.055)	(0.043)	(0.064)	(0.170)
Obs.	3,264	3,891	3,738	3,277
Panel D: Secondary Residence Loans, Log(Loan Amount Originated)				
Post $\times$ Areas of Unprotected Biodiversity Importance	-0.092	0.050	0.055	-0.318
	(0.113)	(0.147)	(0.263)	(0.495)
Obs.	3,264	3,891	3,738	3,277
For All Panels				
Controls	✓	✓	✓	✓
County FEs	✓	✓	✓	✓
State $\times$ Year FEs	✓	✓	✓	✓

Table 12: **Impact of Biodiversity Regulatory Risk on Land and Property Values Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and land and property value measures from Davis et al. (2021) within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). Land and property value measures from Davis et al. (2021) are derived using Uniform Residential Appraisal Report submissions to the Government Sponsored Enterprises (GSEs), Fannie Mae and Freddie Mac and then subtracting an estimate of depreciated replacement cost of the housing structure. The sample period is from 2017 to 2022. Land and property values are at the county $\times$ year level. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 includes counties with the least land available for building, while Quartile 4 includes those with the most. The first four columns Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Land Availability Quartile 1	Land Availability Quartile 2	Land Availability Quartile 3	Land Availability Quartile 4
Panel A: Log(Land Value Per Acre)				
Post $\times$ Areas of Unprotected Biodiversity Importance	0.014	0.025	0.035	0.462***
	(0.061)	(0.048)	(0.072)	(0.152)
Obs.	1,596	1,566	1,548	942
Panel B: Log(Property Value Per Acre)				
Post $\times$ Areas of Unprotected Biodiversity Importance	-0.021	0.022	0.013	0.295***
	(0.035)	(0.026)	(0.037)	(0.084)
Obs.	1,596	1,566	1,548	942
For All Panels				
Controls	✓	✓	✓	✓
County FEs	✓	✓	✓	✓
State $\times$ Year FEs	✓	✓	✓	✓

Table 13: **Impact of Biodiversity Regulatory Risk on Building Permits Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and building permit data from the Census building permits survey within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). The sample period is from 2017 to 2024. We use three measures from the building permits survey as outcomes. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 has the least land available for building while Quartile 4 has the most land available for building. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Land Availability Quartile 1	Land Availability Quartile 2	Land Availability Quartile 3	Land Availability Quartile 4
Panel A: Building Permits - Log(Buildings)				
Post × Areas of Unprotected Biodiversity Importance	0.213	-0.293	-0.144	0.138
	(0.231)	(0.238)	(0.267)	(0.665)
Obs.	3,392	3,956	4,219	4,143
Panel B: Building Permits - Log(Units)				
Post × Areas of Unprotected Biodiversity Importance	0.171	-0.233	-0.313	0.301
	(0.248)	(0.254)	(0.285)	(0.652)
Obs.	3,392	3,956	4,219	4,143
Panel C: Building Permits - Log(Value)				
Post × Areas of Unprotected Biodiversity Importance	0.134	-0.372	-0.309	0.238
	(0.255)	(0.248)	(0.265)	(0.678)
Obs.	3,392	3,956	4,219	4,143
For All Panels				
Controls	✓	✓	✓	✓
County FEs	✓	✓	✓	✓
State × Year FEs	✓	✓	✓	✓

Internet Appendix for:

“Biodiversity Protection Policy and Housing Markets: Supply, Demand, and Speculation”

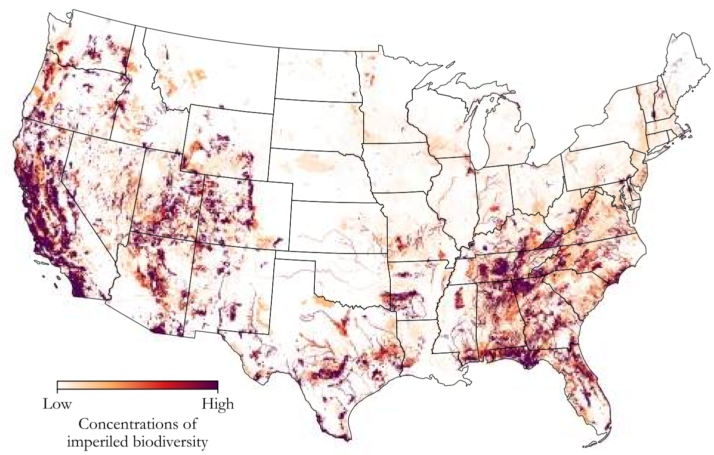
Maxwell Sacher and Shikhar Singla

A Additional Figures and Tables

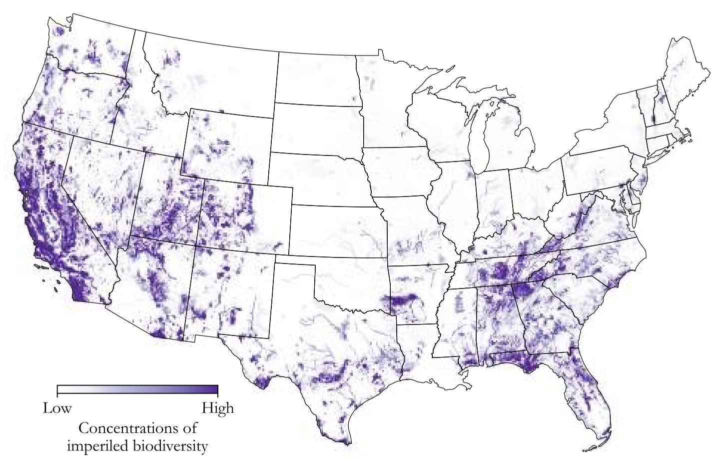
Figure IA.1: **Measures of Endangered Biodiversity**

This figure shows the primary measures of biodiversity regulatory risk that we adopted from NatureServe. Panel A shows the main continuous measure, Protection-weighted Range-size Rarity (PWRSR). Panel B shows range-size rarity, which is the inverse of the modeled habitat area. Panel C shows the main binary measure, which is the Areas of Unprotected Biodiversity Importance (AUBIs). For each species, PWRSR is the product of two components: range-size rarity and the percentage of this habitat that lies outside protected areas. AUBIs are all map pixels with a summed PWRSR of 0.0005 or greater—a threshold set to identify areas with notable conservation importance. This PWRSR value of 0.0005 corresponds to a single species with a 500 km² range that is 25% unprotected, or a species with a smaller range of 20 km² that is 1% unprotected, or even multiple co-occurring species with lower individual PWRSR values. Both PWRSR and AUBI metrics are determined at a resolution level of 990 meters, providing a detailed spatial scale for biodiversity regulatory risk.

Panel A: Protected Weighted range-size rarity (PWRSR)



Panel B: range-size rarity (PSR)



Panel C: Areas of Unprotected Biodiversity Importance (AUBIs)

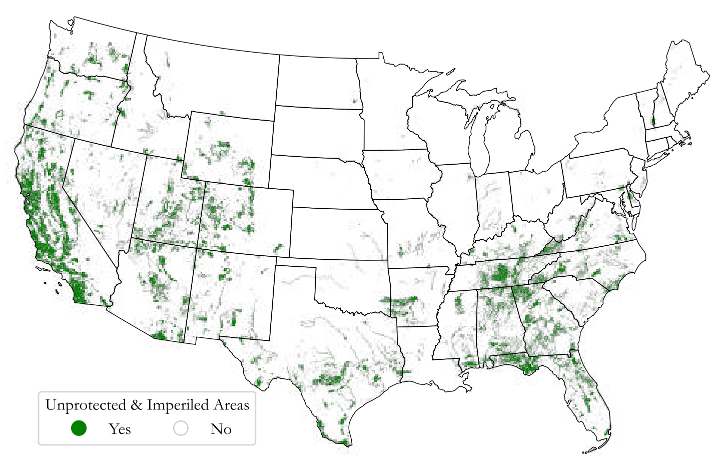
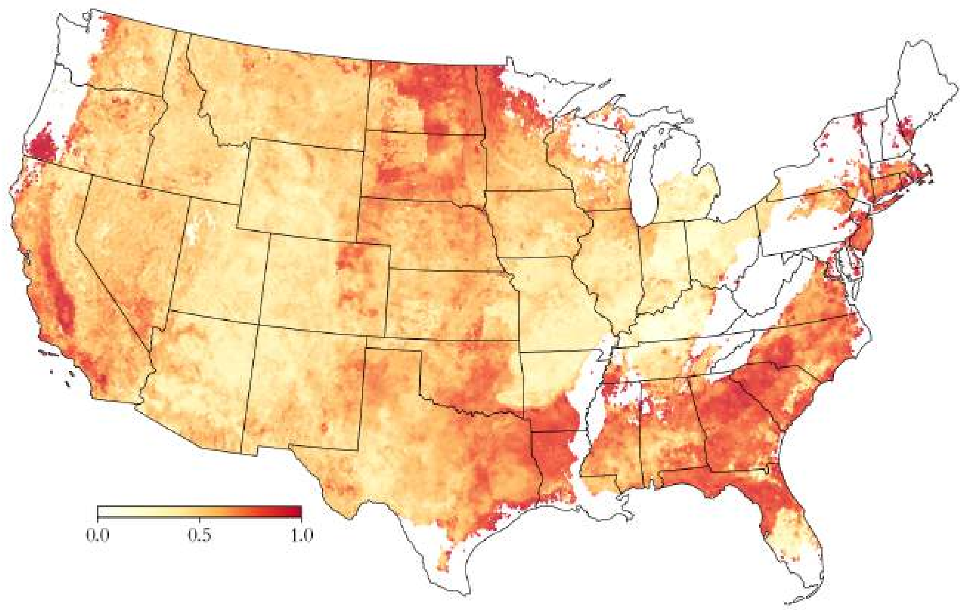


Figure IA.2: **Climate Change Exposure**

This figure shows the spatial distribution of climate change exposure, as measured by NatureServe's climate risk metrics, for mid to late century (Panel A) and near century (Panel B) scenarios across the continental United States. Climate change exposure represents the extent to which natural habitats are projected to experience significant changes in temperature and precipitation patterns, based on six key variables. Scores range from 0 (low exposure) to 1 (high exposure), where higher values indicate areas with greater sensitivity to climate shifts.

Panel A: Climate Exposure Mid to Late Century



Panel B: Climate Exposure Near Century

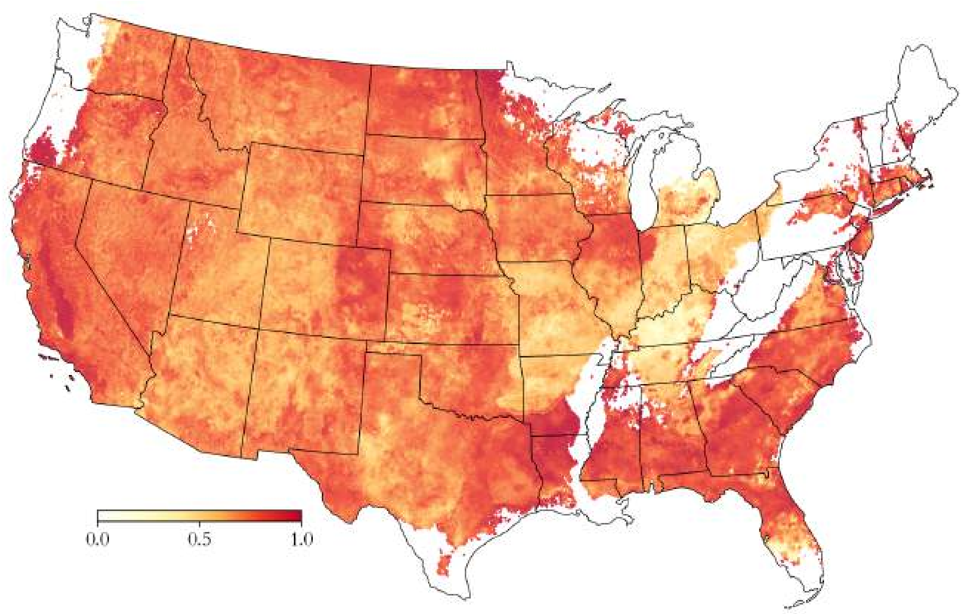
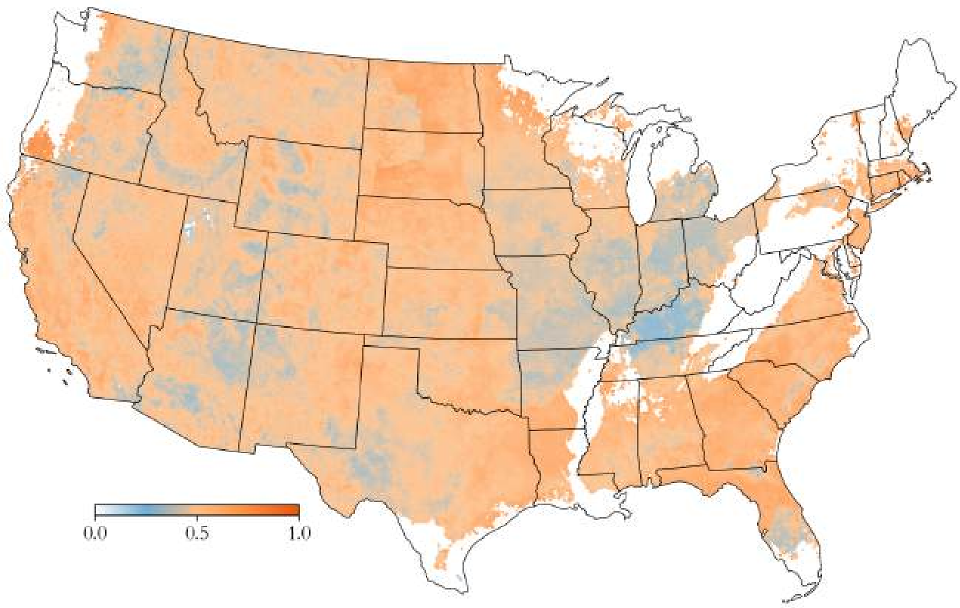


Figure IA.3: **Habitat Climate Change Vulnerability Index (HCCVI)**

This figure shows the spatial distribution of the Habitat Climate Change Vulnerability Index (HCCVI) scores for mid to late century (Panel A) and near century (Panel B) scenarios across the continental United States. The HCCVI score quantifies the vulnerability of natural habitats to climate change, accounting for factors such as exposure to climatic shifts, sensitivity of the habitat to those changes, and adaptive capacity of the ecosystem. Scores range from 0 (low vulnerability) to 1 (high vulnerability), where higher scores indicate areas more at risk of habitat degradation or loss due to climate change.

Panel A: HCCVI Score Mid to Late Century



Panel B: HCCVI Score Near Century

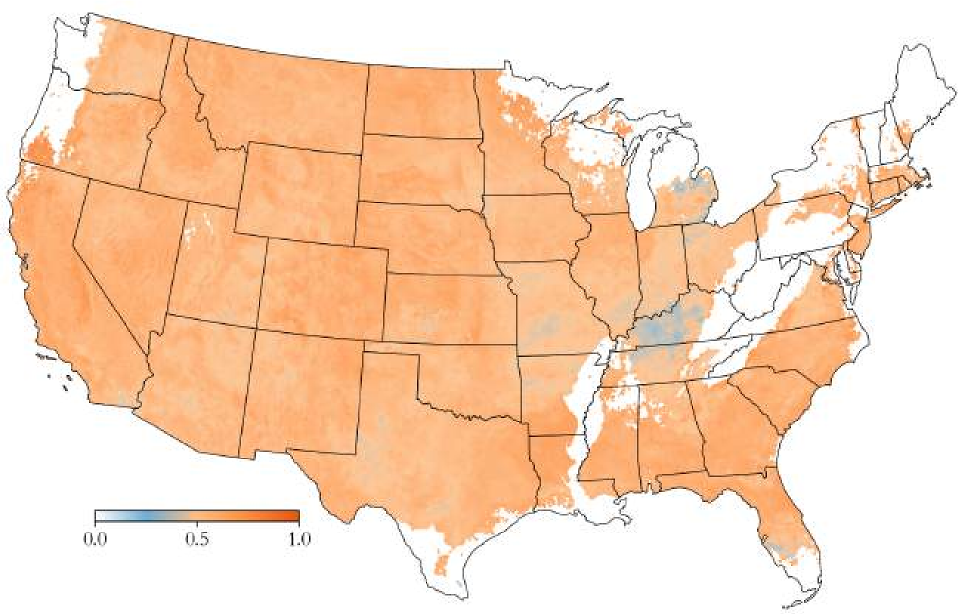


Figure IA.4: **Dynamics for Impact of Biodiversity Regulatory Risk on Housing Prices and PWRSR: MSA**

This figure tests the assumption of parallel trends. We implement Equation 2. The vertical lines signify the start of Biden's presidency and the signing of the *30 by 30* initiative. We compare MSA's in the top tercile of AUBI exposure with those in the bottom tercile before and after the signing. The coefficient represents the percent difference in house prices. The dots indicate point estimates, and the vertical lines indicate 95% confidence intervals.

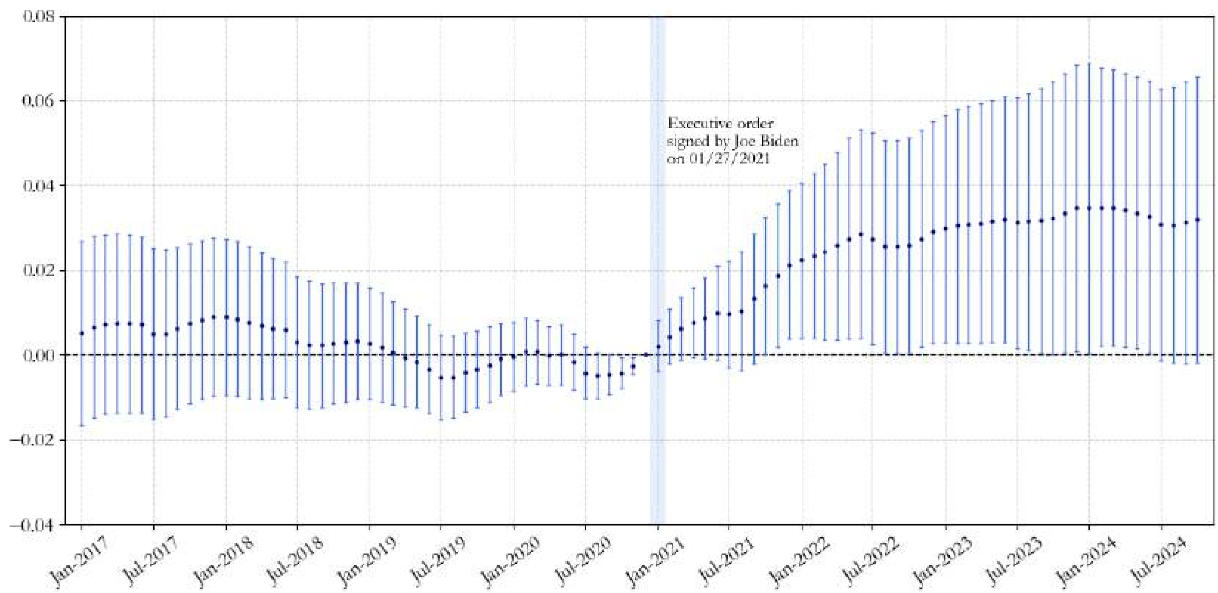
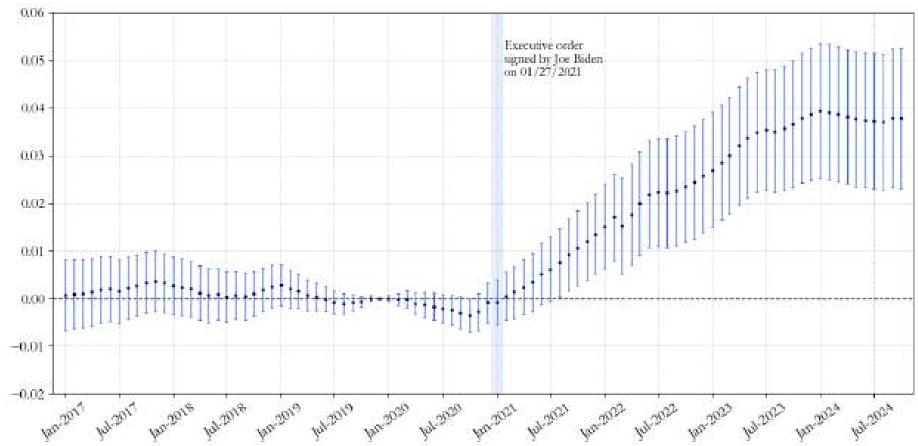
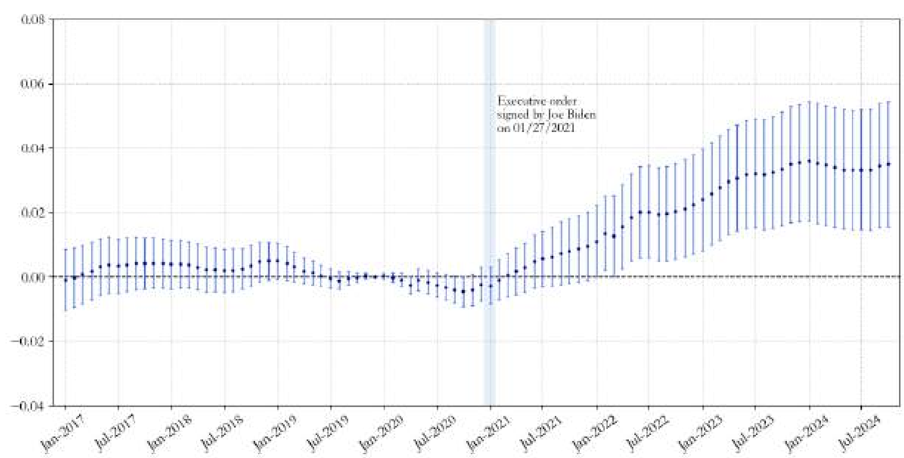


Figure IA.5: **Impact of Biodiversity Regulatory Risk on House Prices: Dynamics using 2019 as the Reference Period**

This figure tests the parallel trends assumption by plotting dynamic coefficients from a specification regressing the log of Zillow Home Value Index on indicators for top-tercile AUBI exposure. We implement a dynamic version of Equation 2. Panels A and B compare treated (top tercile) to control (bottom tercile) counties across two alternative biodiversity measures without including our triple interaction. We include the full set of controls and fixed effects for county and state $\times$ year-month. The vertical line indicates the signing of Executive Order 14008. Coefficients represent percent differences in home prices. Blue dots show point estimates for $Post \times Exposure$; vertical lines are 95% confidence intervals. Standard errors are clustered at the county level. Panel A plots dynamic treatment effects using the AUBI biodiversity measure with December 2019 as the reference period. Panel B displays coefficients from the PWRSR biodiversity measure specification, also using December 2019 as the reference period.



Panel A: AUBI Measure, December 2019 Reference

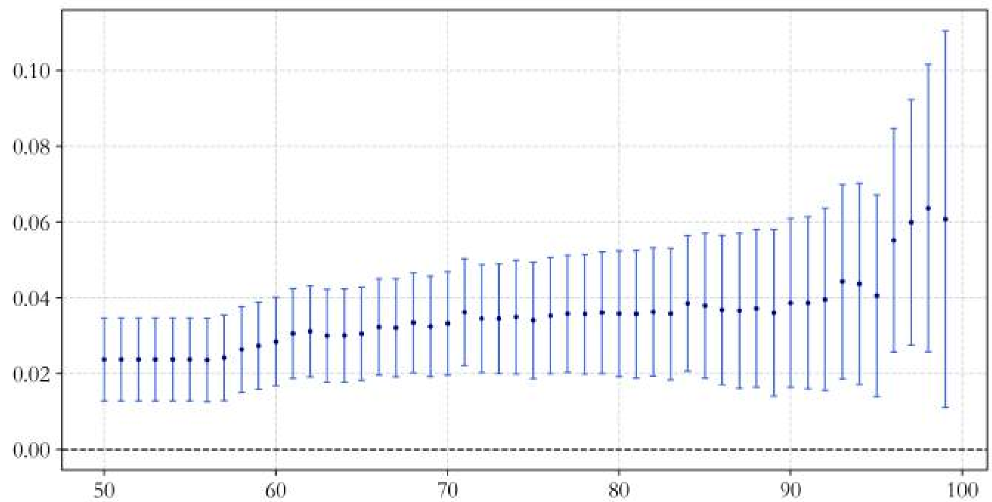


Panel B: PWRSR Measure, December 2019 Reference

Figure IA.6: **Robustness to Treatment Definition**

This figure plots coefficient estimates from the main regression specification, Equation 2, as we vary the definition of treatment based on percentiles of county-level biodiversity regulatory risk (PWRSR, AUBI). We compare the top $x\%$ of counties (high AUBI) to the bottom $1-x\%$ (low AUBI), where x ranges from 50 to 99 on the horizontal axis. For our main results in the paper we set x=66. Each point represents the estimated treatment effect comparing those two groups, with 95% confidence intervals shown. Panel (A) varies our treatment using our AUBI measure. Panel (B) varies our treatment using our PWRSR measure. Regressions are run using the full set of controls as well as county, and state $\times$ year-month fixed effects. Standard errors are clustered at the county level.

Panel A: Varying Treated vs. Control Percentiles, AUBI



Panel B: Varying Treated vs. Control Percentiles, PWRSR

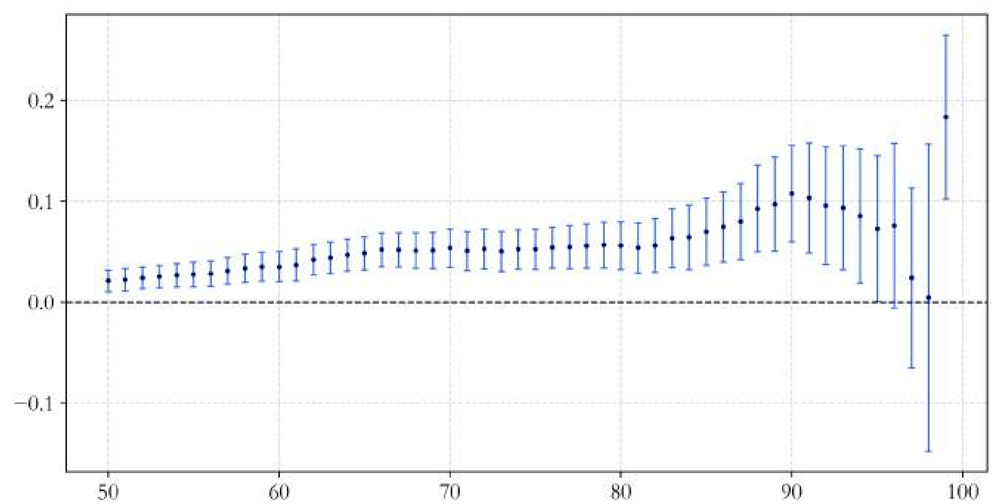
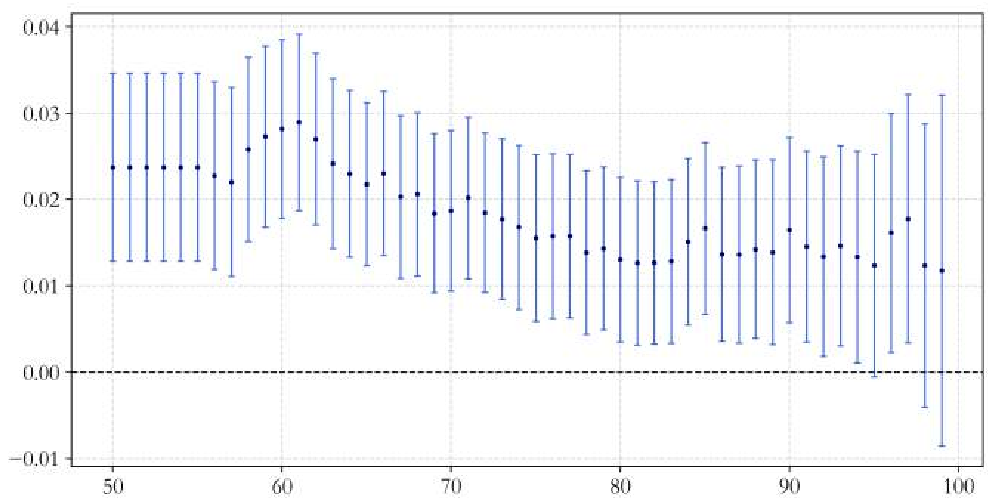


Figure IA.7: **Robustness to Treatment Definition and Sample**

This figure plots coefficient estimates from the from the main regression specification, Equation 2, as we vary the definition of treatment across percentiles of county-level biodiversity regulatory risk (PWRSR, AUBI) but include the full sample in each regression. For each threshold from the 50th to the 99th percentile (x-axis), counties above the threshold are considered treated and those below are considered untreated, and the regression is run on the full sample of counties. Each point represents the estimated treatment effect on log of housing prices, with 95% confidence intervals. Panel (A) varies our treatment using our AUBI risk measure. Panel (B) varies our treatment using our PWRSR risk measure. Regressions are run using the full set of controls as well as county, and state $\times$ year-month fixed effects. Standard errors are clustered at the county level.

Panel A: Varying Treated vs. Control Percentiles, AUBI



Panel B: Varying Treated vs. Control Percentiles, PWRSR

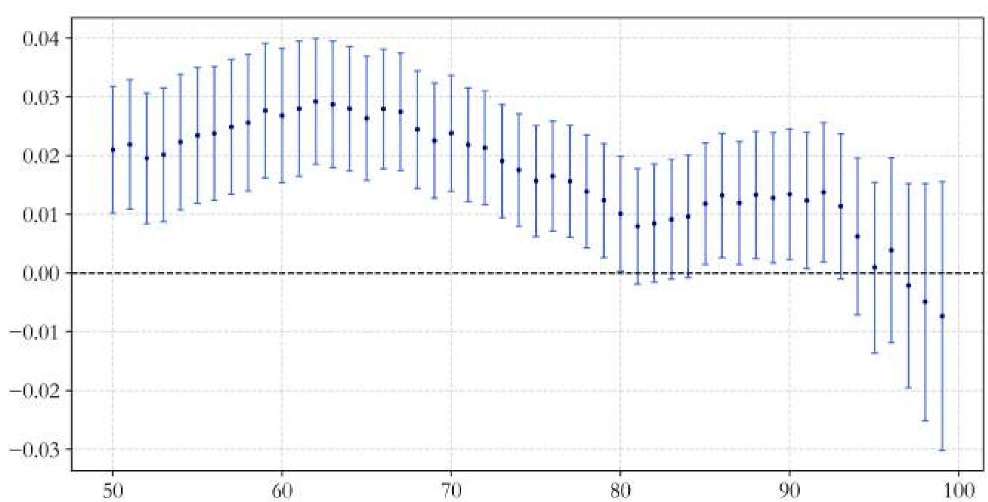


Figure IA.8: **MSA Dynamics with COVID Dynamics**

This figure tests the assumption of parallel trends and independence from dynamic COVID effects. We implement Equation 2 but have both work from home share and biodiversity exposure treated as dynamic. The vertical lines signify the start of Biden's presidency and the signing of the *30 by 30* initiative. We compare MSA's in the top tercile of AUBI exposure with those in the bottom tercile before and after the signing. The coefficient represents the percent difference in house prices. Blue dots show point estimates for *Post* $\times$ *Exposure*. Red dots show point estimates for *Post* $\times$ *Work From Home*. Vertical lines indicate 95% confidence intervals.

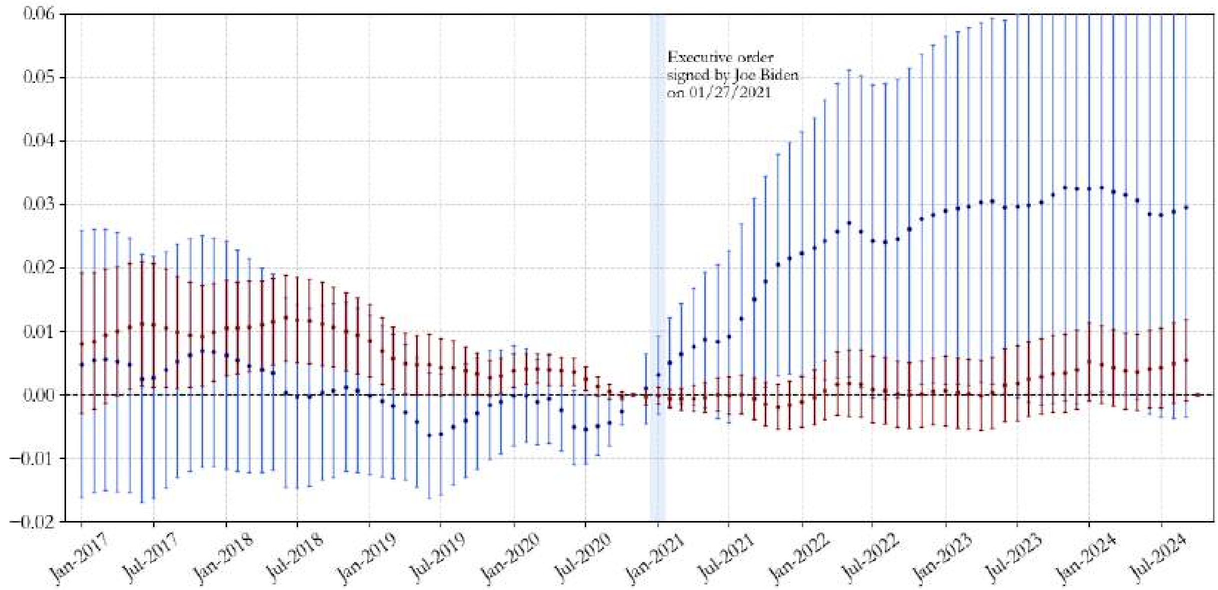
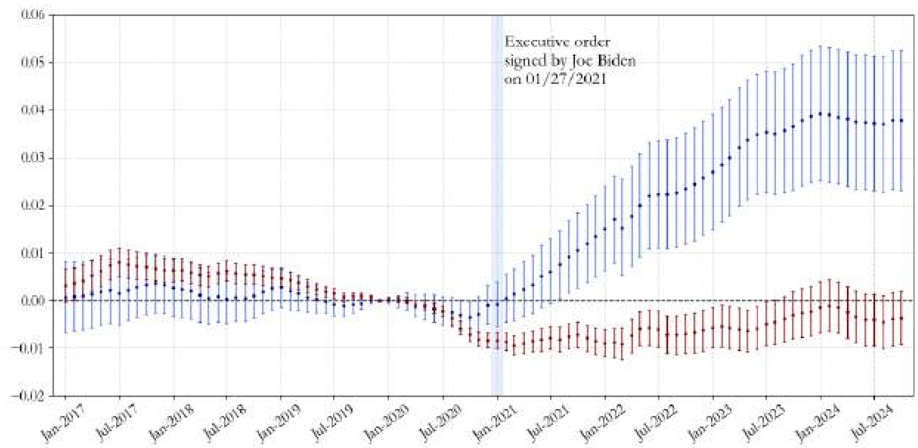
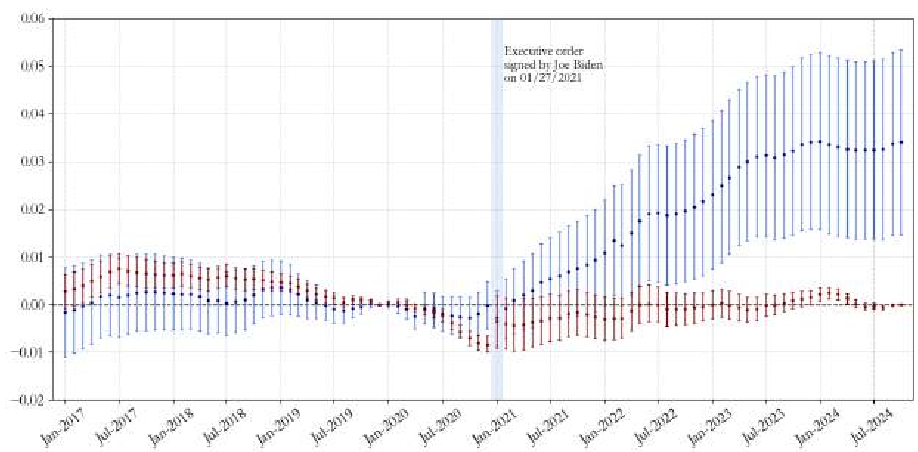


Figure IA.9: **Dynamics using 2019 as the Reference Period including Dynamics for Effects from COVID-19**

This figure tests the parallel trends assumption by plotting dynamic coefficients from a specification regressing the log of Zillow Home Value Index on indicators for top-tercile AUBI exposure. We implement a dynamic version of Equation 2 but have both work from home share and biodiversity exposure treated as dynamic. Panels A and B compare treated (top tercile) to control (bottom tercile) counties across two alternative biodiversity measures. We include the full set of controls and fixed effects for county and state × year-month. The vertical line indicates the signing of Executive Order 14008. Coefficients represent percent differences in home prices. Blue dots show point estimates for *Post* × *Exposure*. Red dots show point estimates for *Post* × *Work From Home*. Vertical lines are 95% confidence intervals. Standard errors are clustered at the county level. Panel A plots dynamic treatment effects using the AUBI biodiversity measure with December 2019 as the reference period. Panel B displays coefficients from the PWRSR biodiversity measure specification, also using December 2019 as the reference period.



Panel A: AUBI Measure, December 2019 Reference



Panel B: PWRSR Measure, December 2019 Reference

Figure IA.10: **Robustness following Oster (2019)**

This figure reports the results of the Oster (2019) robustness analysis. The x-axis shows the assumed increase in the explanatory power of the full model ($R_{\max}$ multiplier), and the y-axis shows the corresponding δ value.

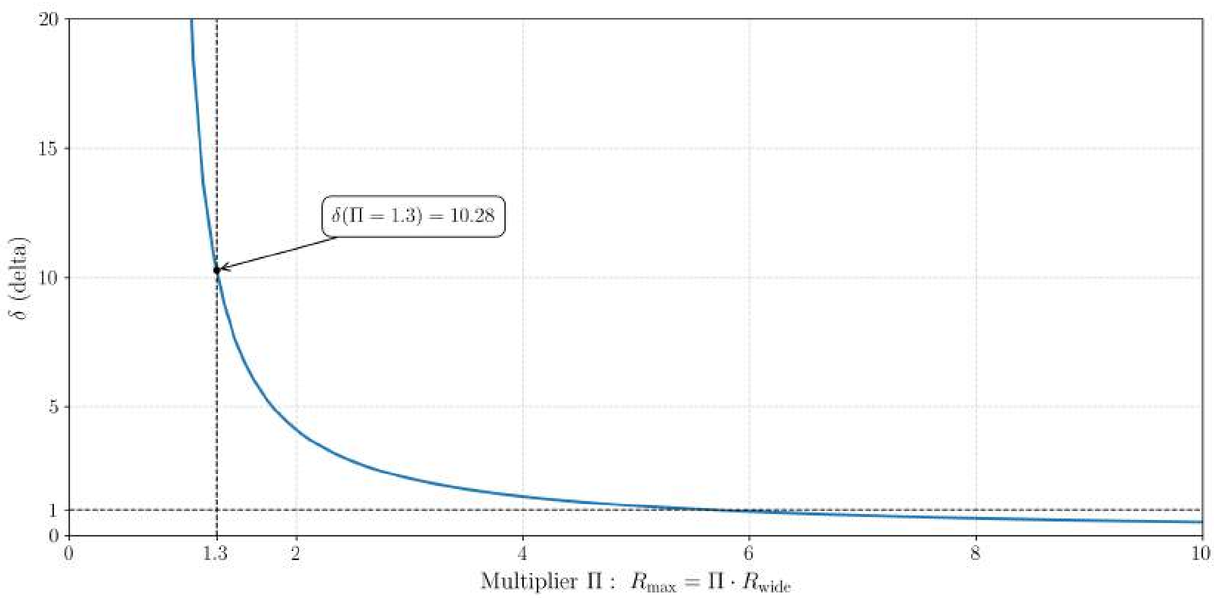
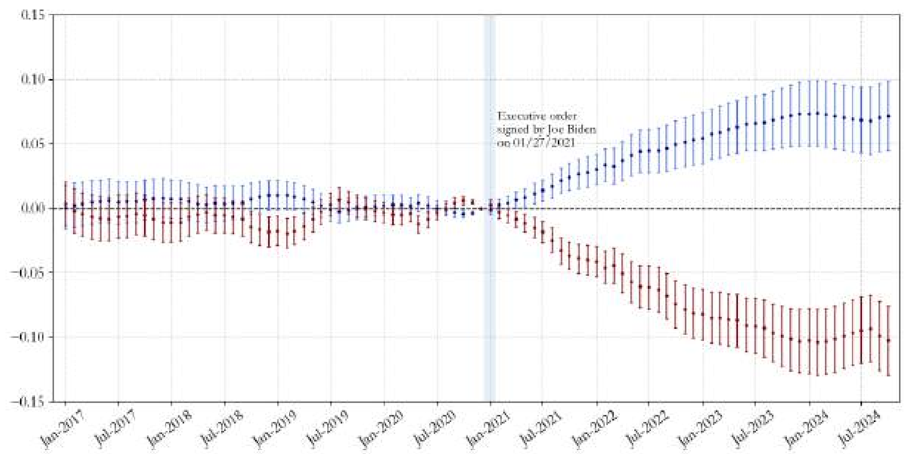
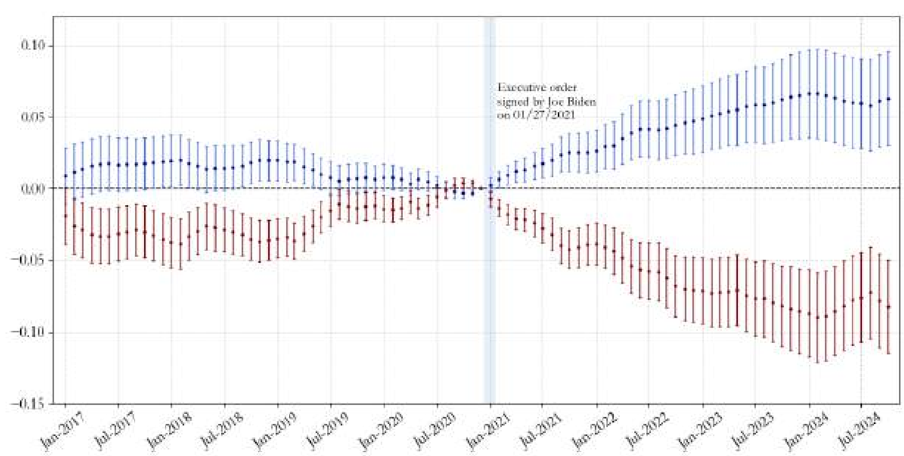


Figure IA.11: **Impact of Biodiversity Regulatory Risk on House Prices: Dynamics with Continuous Triple Difference for Reliance on Nature Intensive Industries**

This figure tests the parallel trends assumption by plotting dynamic coefficients from a specification regressing the log of Zillow Home Value Index on indicators for top-tercile AUBI exposure. We implement a dynamic version of Equation 2. Panels A and B compare treated (top tercile) to control (bottom tercile) counties across two alternative biodiversity measures including a triple interaction with wage share in nature intensive industries. We include the full set of controls and fixed effects for county and state $\times$ year-month. The vertical line indicates the signing of Executive Order 14008. Coefficients represent percent differences in home prices. Blue dots show point estimates for $Post \times Exposure$; vertical lines are 95% confidence intervals. Red dots show point estimates for $Post \times Exposure \times Economic\ Nature\ Dependence$. Standard errors are clustered at the county level. Panel A shows dynamic effects from the discrete AUBI measure with December 2020 as the reference period and includes our discrete measure of nature dependence. Panel B shows dynamic effects from the discrete PWRSR measure with December 2020 as the reference period and includes our discrete measure of nature dependence.



Panel A: AUBI Measure, Continuous Triple Difference

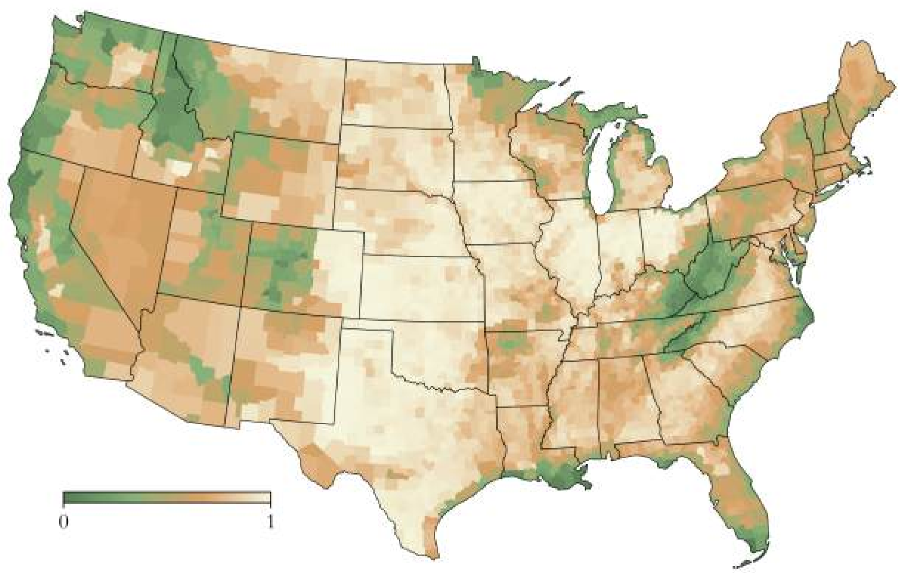


Panel B: PWRSR Measure, Continuous Triple Difference

Figure IA.12: **Geography of Land Availability Measure**

This figure shows Lutz and Sand (2023) measure of land availability. This measure is constructed by dividing the total area of land in a county after removing water bodies, wetlands, and slopes with a greater than 15% grade by the total size of the county. Therefore, counties with higher land availability are less effected by supply shocks and also are lacking in natural projects. Panel A shows the continuous measure of land availability ranging from 0% to 100%. Panel B shows the four quartiles.

Panel A: Continuous Measure



Panel B: Quartiles

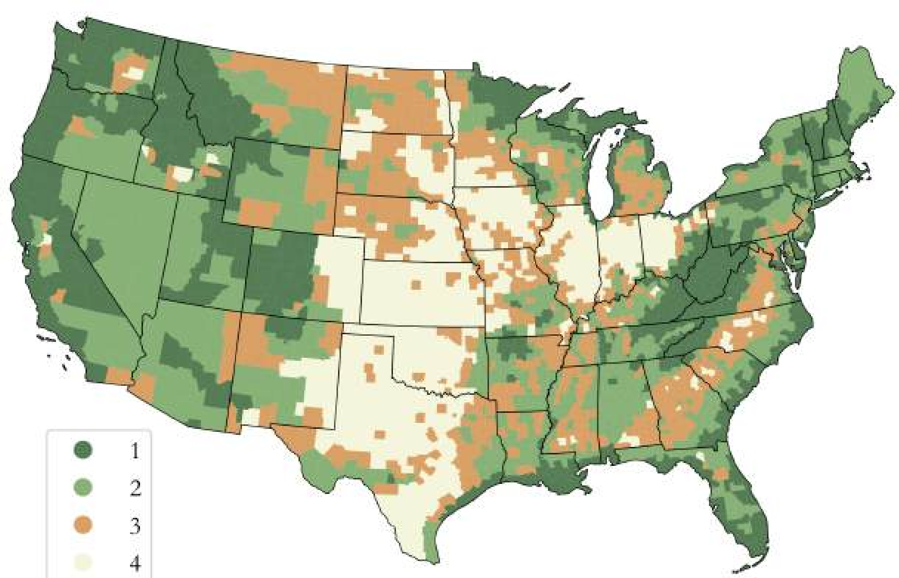


Figure IA.13: **Media Attention of Projects Started Under America the Beautiful**

This figure illustrates the media attention surrounding nature improvments started under the *30 by 30* initiative over time. It presents the unique number of articles mentioning the initiative and projects on a monthly basis. The data was retrieved from Factiva, using an advanced query designed to capture relevant articles discussing America the Beautiful while filtering out unrelated mentions. The query is limited to U.S.-based sources and English-language articles with nature projects as their subject. The query required (1) the mention of "America the Beautiful" in various formats, (2) the inclusion of at least one relevant keyword related to projects, amenities, or specific programs started under the initiative . These details are a large reason we examine post-2020 data primarily- media and investor awareness seem to be driving the relationship. The details of the query and filtering process are provided in Figure IA.14.

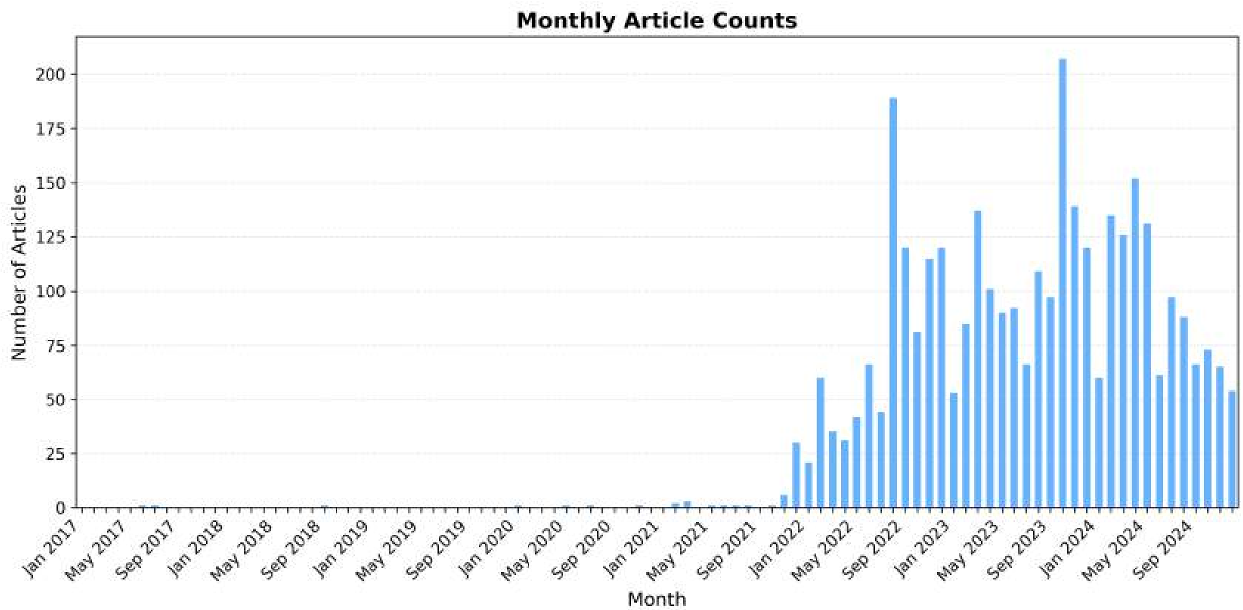


Figure IA.14: **Factiva Search**

This figure shows our search process in Factiva to retrieve relevant articles on the "America The Beautiful" initiative. We present the search filters and the query we used in Factiva. The query excludes Federal reports and is limited to U.S.-based sources and English-language articles with subject “Nature Environment".

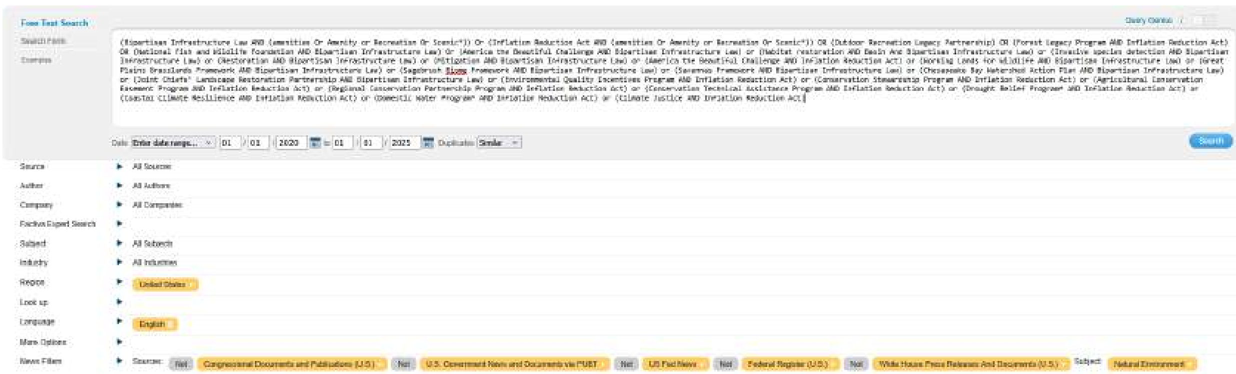
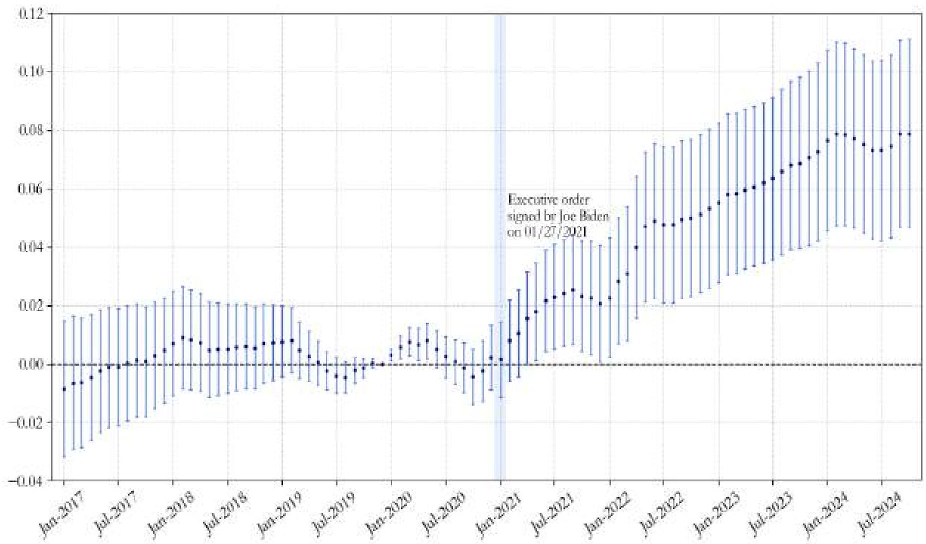
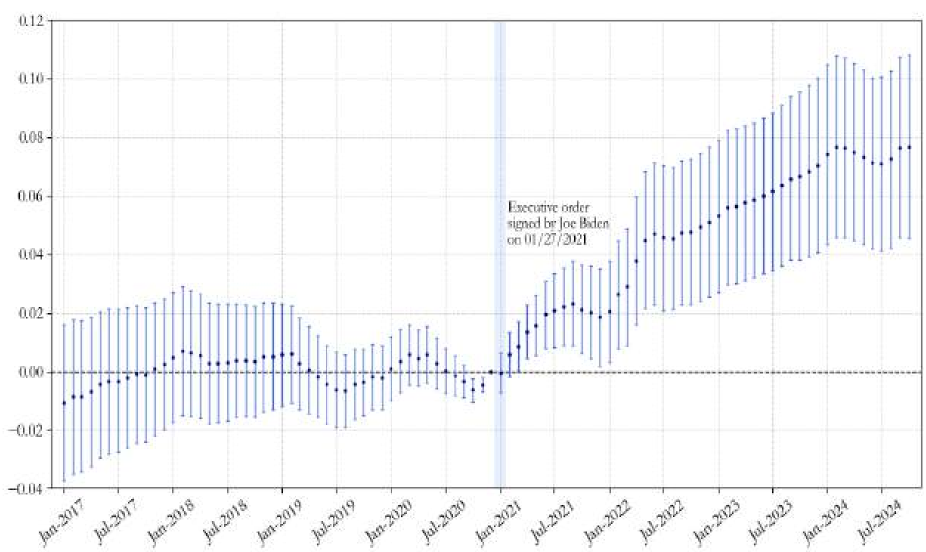


Figure IA.15: **Effect of Continuous Biodiversity Regulatory Risk on House Value: Dynamics**

This figure plots dynamic coefficients from a continuous difference-in-differences specification using the log of Zillow Home Value Index as the outcome variable. The estimates reflect the association between our continuous AUBI biodiversity exposure index and housing values over time. Both panels include controls for Work From Home share, park area, climate risk indices, one month lagged log of employment, and fixed effects for county and state $\times$ year-month. The vertical line marks the signing of Executive Order 14008 on January 27, 2021. Dots represent coefficient point estimates; vertical bars show 95% confidence intervals. Panel (A) uses December 2019 as the reference period for the time indicators in the regression. Panel (B) repeats the analysis with December 2020 as the reference period. Standard errors are clustered at the county level.



Panel (A): December 2019 Reference Month



Panel (B): December 2020 Reference Month

Table IA.1: **Variable Definitions and Sources**

Variable	Definition	Source
Biodiversity Regulatory Risk Measures		
Range Size Rarity (RSR)	Inverse of the modeled habitat area for each species. Summed across species to aggregate range-size rarity at the 990 meter grid resolution.	NatureServe
Protection Weighted Range Size Rarity (PWRSR)	Product of species range-size rarity and the percentage of habitat outside protected areas. Summed across species to aggregate PWRSR at the 990 meter grid resolution.	NatureServe
Areas of Unprotected Biodiversity (AUBI)	A binary variable equal to 1 if the summed PWRSR at the geographical level is ≥ 0.0005; otherwise, it equals 0. Data are at a 990-meter resolution.	NatureServe
Main Outcome Variables		
Zillow Home Value Index (ZHVI)	Seasonally adjusted, smoothed measure of the typical home value within a county. It incorporates property-level estimates rather than relying solely on observed sale prices.	Zillow
Zillow Observed Rent Index (ZORI)	Measure developed by Zillow that reflects the typical observed market rent for new leases across rental units within a county. It is based on actual listed rents, not estimates or interpolations	Zillow
Loan Originations	Total value of mortgage loan requests submitted by individuals within a county. We keep only loans whose purpose is "home purchase."	HMDA
Loan Applications	Total value of mortgage loan requests approved and issued within a county. We keep only loans whose purpose is "home purchase."	HMDA
Primary Residence Loan	Loan whose occupancy type is reported as "primary residence." We keep only loans whose purpose is "home purchase."	HMDA
Secondary Residence Loan	Loan whose occupancy type is reported as "secondary residence." We keep only loans whose purpose is "home purchase."	HMDA
Investment Loan	Loan whose occupancy type is reported as "investment." We keep only loans whose purpose is "home purchase."	HMDA
Land Value ($/acre)	Estimated land value net of structures. Can be either regular or standardized.	Davis et al. (2021)
Property Value ($/acre)	Total market value of a residential parcel, including both the land and the physical structure(s) on it. Can be either regular or standardized.	Davis et al. (2021)
Yearly Average Change in Park Visits	Measure of how much visitation to parks in a county changed, on average, relative to 2019. Percent change in park visits averaged over each year for each county.	Google Mobility Reports
Buildings	Total number of new residential building permits issued in a county in a given month. Can be either true reported amount or imputed.	Census Bureau's Building Permits Survey
Units	Total number of housing units associated with newly issued residential building permits in a county in a given month. Can be either true reported amount or imputed.	Census Bureau's Building Permits Survey
Value	Estimated total construction cost of all residential building permits issued in a county in a given month. Can be either true reported amount or imputed.	Census Bureau's Building Permits Survey
Validation Outcome Variables		
Has Project	Equals 1 if a county received at least one conservation-related government project under the IRA or BIL; 0 otherwise.	IRA & BIL
Number of Projects	Count of all conservation-related government projects under the IRA or BIL located within a county.	IRA & BIL

Funded Project	Equals 1 if a county received at least one conservation-related project that was actually funded; 0 otherwise.	IRA & BIL
Total Funding	Sum of dollar amounts allocated to conservation-related projects within a county.	IRA & BIL
Easement Received	Equals 1 if any conservation easement started after 2021 intersects the county boundary; 0 otherwise.	NCED
Number of Easements	Count of all conservation easements started after 2021 that intersect a county's geographic area.	NCED
Conservation Easement Received	Equals 1 if a conservation easement (purpose labeled as environmental, scenic, or recreation) started after 2021 intersects the county; 0 otherwise.	NCED
Number of Conservation Easements	Count of conservation easements (purpose labeled as environmental, scenic, or recreation) started after 2021 intersecting the county; 0 otherwise.	NCED
	Control Variables	
Wage Share from Nature-dependent Industries	Calculated as the proportion of wages in a county that come from industries with NAICS codes equal to or less than 33. We calculate a single value for each county using monthly data from 2017 - 2020.	Self-constructed using Quarterly Census of Employment and Wages (QCEW)
Climate Exposure Near Century	Measures climate-induced stress on ecosystems within spatial units over 100 square kilometers. Scores range from 0.0 (highest stress) to 1.0 (lowest stress), with projections for near-century.	NatureServe
Climate Exposure Mid Century	Same as above, but for mid 21st century.	NatureServe
HCCVI Near Century	Assesses habitat vulnerability based on exposure, sensitivity, and adaptive capacity within spatial units over 100 square kilometers. Scores range from 0.0 (highest vulnerability) to 1.0 (lowest vulnerability), with projections for near-century.	
HCCVI Mid Century	Same as above, but for mid 21st century	NatureServe
HCCVI Mid Century	Same as above, but for mid 21st century	
Monthly COVID Infections	Sum of a County's new reported cases of infections by COVID-19	Center for Disease Control
Net Migration	Yearly net migration into a county. Inflows are treated as positive and outflows as negative and the flows is summed to create a net migration.	Statistics of Income
Land Available (%)	Land Available is a county-level measure of the share of land that is physically suitable for development. It is constructed by removing wetlands, water bodies, and areas with slopes greater than 15% from the total land area.	Lutz and Sand (2023)
Land Buildable (%)	Land Buildable is a county-level measure of the share of land that is physically suitable for development It is constructed by removing not parks, wetlands, water bodies, and steep slopes (greater than 15%), and already developed areas.	Lutz and Sand (2023)
Area Wetlands (%)	Share of county classified as wetlands	Lutz and Sand (2023)
Total Park Area (%)	Share of land designated as public parkland	TomTom
Work From Home	Share of employed individuals working remotely	ACS
County Land Area	Total land area of the county (sq km)	U.S. Census TIGER
County Water Area	Total inland water area of the county (sq km)	U.S. Census TIGER
Land Area Urban (%)	Percent of land area classified as urbanized or urban cluster	U.S. Census TIGER

Nature Deprivation Score	The score is based on spatial data indicating the availability of natural amenities such as parks, open space, urban forests, tree canopy, waterways, and beaches. A higher score indicates greater deprivation. The county-level measure is created by aggregating tract-level scores	CEQ
Employment	Total number of individuals employed in a given county in a given month	Quarterly Census of Employment and Wages (QCEW)
County GDP	Total economic output produced within a county. It encompasses all industry sectors and includes private and public economic activity.	Bureau of Economic Analysis (BEA)

Table IA.2: **Description of Additional Datasets Used in the Analysis**

Dataset	Description
House Price Data	For our main outcome variable, we use the Zillow Home Value Index (ZHVI). The Zillow Home Value Index (ZHVI) estimates the value of a typical property within a specified geographic boundary based on a combination of transactions and imputed property value estimates. The index is seasonally adjusted and smoothed using a three-month moving average. We use county-level ZHVI data for single-family residences. ZHVI incorporates property-level estimates rather than relying solely on observed sale prices, allowing for a more comprehensive measure of housing market trends, even in areas with low transaction volumes.
Inflation Reduction Act and Bipartisan Infrastructure Law	To validate our biodiversity measure, we use data on federal conservation projects initiated in response to the *30 by 30* initiative under the Inflation Reduction Act (IRA) and Bipartisan Infrastructure Law (BIL). The data contains information on the type of government project, its centroid location, as well as the amount of funding allocated to the project. We exclude projects that are unrelated to biodiversity protection, as well as those where the recorded location reflects the administrative office rather than the actual area of management.
National Conservation Easement Database	We supplement our dataset with information from the National Conservation Easement Database (NECD). A conservation easement is an agreement to restrict certain types of land use to advance conservation goals. For example, instead of purchasing a forest outright, a land trust may contract with the owners to acquire only the extraction rights and retire them to conserve the area. This represents a less costly alternative to full land acquisition for achieving conservation goals. NECD works with both private and public agencies to collect information on the establishment date, purpose, and area of recorded conservation easements.
Quarterly Census of Employment and Wages	In order to explore heterogeneity within our sample and control for changing economic conditions, we use the Quarterly Census of Employment and Wages. The Quarterly Census of Employment and Wages (QCEW) collects quarterly counts of employment and wages reported by employers. They cover more than 95 percent of U.S. jobs available at the county level by industry. In order to get a measure of a county's dependence on nature-intensive industries, we divide the total wages in industries with two-digit NAICS codes less than or equal to 33 by the total wages earned in a county over the pre-period of our sample, from 2017 to 2020. We also use as a control the natural log of total employment in a county to account for changing economic conditions that could be correlated with biodiversity regulation.
Center for Disease Control COVID-19 Surveillance Data	We use data compiled by the Center for Disease Control, which collects daily reports of confirmed COVID-19 cases from state and local health departments. These data are aggregated into a standardized time series that includes both cumulative and daily new case counts at the state and county level. Historical revisions issued by health authorities are incorporated into the dataset, and the full series is made publicly available through the Center for Disease Control repository: `https://data.cdc.gov/Case-Surveillance/COVID-19-Case-Surveillance-Public-Use-Data-with-Ge/n8mc-b4w4/about_data`.

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Dataset	Description
Statistics of Income Migration Data	We use data from the IRS "SOI Tax Stats — Migration Data," which are derived from year-to-year address changes reported on U.S. individual income tax returns. The data include, for filing years 1991 to 2022, counts of tax returns as a proxy for migrating households and numbers of personal exemptions as a proxy for individuals by origin and destination giving both total inflows and outflows at the county level. We sum both total inflows and outflows for individuals for each county in each year to get a measure of net migration.
Land Availability	To disentangle supply and demand effects, we focus on areas where housing supply is unconstrained and demand is high. We use the land unavailability measure developed by Lutz and Sand (2023). The measure is calculated by subtracting parkland, wetlands, and steeply sloped areas from a county's total land area, and then dividing the available portion by the county's total area. This provides a measure of a county's sensitivity to supply shocks. Areas with little land availability are highly sensitive to such shocks, while those with ample land availability are relatively unaffected. Moreover, because the measure excludes natural areas such as parks, areas with high land availability also tend to have fewer existing nature projects and therefore exhibit a higher marginal demand for environmental improvements.[19]
Measures of Supply and Demand	We further validate our findings by using other measures of both supply and demand. On the demand side, we use HMDA loan application data, focusing on the value of loan applications and originations. We further divide the data between applications intended for primary or secondary residences and those for investment properties. We also use Google Mobility Reports as a proxy for increased demand. On the supply side, we use housing permits data from the U.S. Census Bureau. This yearly survey reports the number of newly issued permits, along with the number of new units, buildings, and their associated construction values.
Protected Areas	We utilize spatial data on protected lands from the U.S. Geological Survey's Protected Areas Database of the United States (PAD-US), a comprehensive repository detailing ownership, conservation status, and management objectives for protected areas nationwide. Our analysis focuses on lands classified under GAP Status 1 and 2, which are explicitly designated for the conservation of biodiversity. GAP Status 1 areas are subject to the highest level of protection, with management practices aimed at preserving natural ecosystems and prohibiting all extractive uses. GAP Status 2 areas similarly prioritize biodiversity conservation but may permit limited human activities, provided they do not compromise the ecological integrity of the site.

[19] Two other measures are also available. Baum-Snow and Han (2024) and Gyourko et al. (2008) each construct housing supply elasticity measures for a set of U.S. metropolitan areas. However, these measures are not sufficiently comprehensive for our analysis. Furthermore, their construction does not capture the interaction between rising demand for natural improvements and diminishing supply, an interaction central to our empirical strategy.

Table IA.3: **Biodiversity and Government Projects**

This table shows summary statistics for government projects as well as their relationship with locations that are Areas of Unprotected Biodiversity. The first column reports totals for both project counts and funding. Conservation projects are defined as projects with atlas category “Resilience and Ecosystem Restoration" or “America the Beautiful Challenge Grants" or who’s program name mentions “Conservation." The next columns expand the size of Areas of Unprotected Biodiversity by 1 km along each edge, making grids a total of $2km^2$. The values represent the sum of values that fall within an Area of Unprotected Biodiversity. We report both the sum and percent of total that falls within each area. The next two columns repeat this exercise, but expand the grid by 5km and 10km respectively.

		Distance from AUBI					
	Total Projects	< 2km		< 5km		< 10km	
		Count	%	Count	%	Count	%
Project Counts	2,112	395	18.7	789	37.4	985	46.6
Project Funding	\$6.00 bil	\$1.20 bil	20.0	\$2.46 bil	41.0	\$3.01 bil	50.2
Conservation Project Counts	797	135	16.9	263	33.0	349	43.8
Conservation Project Funding	\$1.33 bil	\$0.16 bil	12.1	\$0.27 bil	20.2	\$0.34 bil	25.8
BIL Project Counts	1,348	270	20.0	503	37.3	632	46.9
BIL Project Funding	\$3.48 bil	\$0.58 bil	16.7	\$1.01 bil	29.1	\$1.44 bil	41.3
IRA Project Counts	764	125	16.4	286	37.4	353	46.2
IRA Project Funding	\$2.51 bil	\$0.61 bil	24.5	\$1.44 bil	57.5	\$1.57 bil	62.4

Table IA.4: **Impact of Biodiversity Regulatory Risk on House Value at the MSA Level**

This table examines the relationship between counties' exposure to biodiversity regulatory risk and home value at the MSA level (Equation 2). The sample period is from 2017 to 2024. The outcome variable is the log of the Zillow Home Value Index at the MSA level. Columns (1), (3), and (5) use Protection Weighted range-size rarity as our measure of risk. Columns (2), (4), and (6) use our Area of Unprotected Biodiversity Importance to measure biodiversity regulatory risk. We use a continuous measure of biodiversity regulatory risk in all columns. Columns (1) and (2) focus solely on the difference-in-difference measures. Columns (3) and (4) incorporate controls for Work From Home and Total Park Area, our climate exposure measures, as well as county and month fixed effects. Columns (5) and (6) present the full model, which includes all explanatory variables, as well as county, month, and state × year-month fixed effects. Columns (7) and (8) present the full model, but using the log of our continuous measure for our measure of exposure to biodiversity regulatory risk. Standard errors are clustered at the county level and reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Zillow Home Value Index)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Protection Weighted Range Size Rarity × Post	23.038***		10.552*		2.707			
	(8.281)		(6.092)		(4.456)			
Areas of Unprotected Biodiversity Importance × Post		0.144***		0.093***		0.046*		
		(0.028)		(0.025)		(0.025)		
Log(Protection Weighted Range Size Rarity) × Post							0.008***	
							(0.003)	
Log(Areas of Unprotected Biodiversity Importance) × Post								-0.002
								(0.004)
Protection Weighted Range Size Rarity	297.844***							
	(34.503)							
Areas of Unprotected Biodiversity Importance		1.089***						
		(0.167)						
Post	0.318***	0.311***						
	(0.005)	(0.006)						
Post × Total Park Area (%)			0.100***	0.087***	0.060***	0.056**	0.050**	0.059**
			(0.024)	(0.024)	(0.022)	(0.022)	(0.022)	(0.026)
Post × Work From Home			-0.411***	-0.415***	-0.175*	-0.190*	-0.200*	-0.181
			(0.101)	(0.099)	(0.101)	(0.099)	(0.102)	(0.118)
Post × Climate Exposure Near Century			-0.363***	-0.366***	0.003	0.008	-0.045	-0.038
			(0.087)	(0.086)	(0.079)	(0.078)	(0.081)	(0.163)
Post × Climate Exposure Mid to Late Century			0.157***	0.149***	0.059*	0.059*	0.070**	0.102
			(0.036)	(0.036)	(0.036)	(0.035)	(0.035)	(0.070)
Post × Habitat Climate Change Vulnerability Index			0.331**	0.335**	-0.129	-0.138	-0.058	-0.169
			(0.149)	(0.151)	(0.129)	(0.128)	(0.133)	(0.265)
Log(Employment)			0.305***	0.294***	0.162***	0.164***	0.159***	0.145***
			(0.040)	(0.039)	(0.032)	(0.032)	(0.032)	(0.042)
Adj. R-squared	0.249	0.217	0.988	0.988	0.994	0.994	0.994	0.995
Obs.	56,600	56,600	51,484	51,484	51,108	51,108	50,733	26,694
County FEs			✓	✓	✓	✓	✓	✓
Year-Month FEs			✓	✓	✓	✓	✓	✓
State × Year-Month FEs					✓	✓	✓	✓

Table IA.5: **Impact of Biodiversity Regulatory Risk on Observed Rent Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and the log of Zillow Observed Rent Index within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). The sample period is from 2017 to 2024. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 has the least land available for building while Quartile 4 has the most land available for building. The first four columns (1) - (4) present regressions only controlling for county, month, and state × year-month fixed effects. Columns (5) - (8) add in our COVID and climate related controls. Columns (9) - (12) hold fixed the sample, but change the outcome variable to our main outcome in the paper, Zillow home value index. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Rent)								Log(House Prices)			
	(1) Land Availability Quartile 1	(2) Land Availability Quartile 2	(3) Land Availability Quartile 3	(4) Land Availability Quartile 4	(5) Land Availability Quartile 1	(6) Land Availability Quartile 2	(7) Land Availability Quartile 3	(8) Land Availability Quartile 4	(9) Land Availability Quartile 1	(10) Land Availability Quartile 2	(11) Land Availability Quartile 3	(12) Land Availability Quartile 4
Post × AUBI	-0.039	-0.046	-0.029	-0.008	-0.027	-0.042	-0.039	0.014	0.020	-0.055	-0.046	0.185*
	(0.055)	(0.044)	(0.040)	(0.081)	(0.047)	(0.047)	(0.039)	(0.076)	(0.045)	(0.045)	(0.046)	(0.094)
Log(Emp)					0.068	0.118	0.052	0.020	0.026	0.245**	0.079	-0.072
					(0.070)	(0.074)	(0.049)	(0.106)	(0.089)	(0.105)	(0.060)	(0.081)
Post × Work From Home					-0.903***	-0.632***	-0.716***	-0.117	-0.782***	-0.488	-0.941***	-0.217
					(0.155)	(0.175)	(0.103)	(0.194)	(0.248)	(0.402)	(0.138)	(0.204)
Post × Climate Near Century					0.091	0.073	0.357**	0.289	0.164	-0.113	0.612**	0.304
					(0.106)	(0.228)	(0.166)	(0.272)	(0.128)	(0.361)	(0.262)	(0.270)
Post × Climate Mid Century					-0.065	-0.130*	-0.013	-0.018	-0.050	-0.192**	-0.000	-0.085
					(0.054)	(0.075)	(0.068)	(0.133)	(0.060)	(0.089)	(0.082)	(0.119)
Post × HCCVI					0.032	0.072	-0.750**	-0.019	-0.253	0.358	-1.286***	0.203
					(0.224)	(0.314)	(0.320)	(0.472)	(0.271)	(0.509)	(0.488)	(0.499)
Adj. R-squared	0.992	0.990	0.992	0.987	0.993	0.991	0.994	0.988	0.996	0.992	0.996	0.993
Obs.	20,905	15,077	14,215	9,470	18,446	12,973	13,394	8,875	18,445	12,972	13,392	8,870
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year-Month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.6: **Summary Statistics Land Availability Quartiles**

This table presents summary statistics split by Land Availability Quartiles as defined by Lutz and Sand (2023).The sample period is from 2017 to 2024. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 includes counties with the least land available for building, while Quartile 4 includes those with the most.

	Level of Observation	Number of Observations	Mean	Std Dev	p5	p25	Median	p75	p95
Panel A: Land Availability Quartile 1									
Protection Weighted Range Size Rarity (PWRSR)	County	774	3.80	7.19	0.01	0.26	1.05	4.11	15.65
Areas of Unprotected Biodiversity (AUBI)	County	774	0.11	0.16	0.00	0.00	0.03	0.15	0.48
Land Available (%)	County	774	0.38	0.15	0.11	0.26	0.40	0.51	0.58
Zillow Home Value Index	County × Month	73,932	266,040.74	209,253.30	85,366.07	141,555.67	210,965.78	325,160.86	609,989.14
Number of IRA & BIL Projects	County	774	0.91	4.03	0.00	0.00	0.00	1.00	4.00
Number of Conservation IRA & BIL Projects	County	774	0.38	1.54	0.00	0.00	0.00	0.00	2.00
Wage Share from Nature-dependent Industries	County	758	30.87%	16.23%	09.12%	19.87%	27.81%	40.43%	61.33%
Panel B: Land Availability Quartile 2									
Protection Weighted Range Size Rarity (PWRSR)	County	767	2.45	4.30	0.02	0.21	0.70	2.56	11.14
Areas of Unprotected Biodiversity (AUBI)	County	767	0.09	0.14	0.00	0.00	0.02	0.11	0.42
Land Available (%)	County	767	0.71	0.06	0.61	0.66	0.72	0.77	0.80
Zillow Home Value Index	County × Month	72,890	193,719.48	109,967.49	82,882.75	123,408.56	166,263.33	231,179.71	394,343.08
Number of IRA & BIL Projects	County	767	0.69	3.43	0.00	0.00	0.00	0.00	3.00
Number of Conservation IRA & BIL Projects	County	767	0.37	2.47	0.00	0.00	0.00	0.00	2.00
Wage Share from Nature-dependent Industries	County	757	35.06%	16.38%	11.31%	22.67%	33.25%	44.96%	63.87%
Panel C: Land Availability Quartile 3									
Protection Weighted Range Size Rarity (PWRSR)	County	756	1.43	2.77	0.01	0.11	0.35	1.44	6.49
Areas of Unprotected Biodiversity (AUBI)	County	756	0.05	0.10	0.00	0.00	0.00	0.06	0.27
Land Available (%)	County	756	0.87	0.03	0.82	0.84	0.87	0.90	0.91
Zillow Home Value Index	County × Month	70,903	184,003.25	93,495.63	82,109.79	119,674.84	160,133.77	221,199.23	363,558.70
Number of IRA & BIL Projects	County	756	0.31	1.15	0.00	0.00	0.00	0.00	2.00
Number of Conservation IRA & BIL Projects	County	756	0.12	0.58	0.00	0.00	0.00	0.00	1.00
Wage Share from Nature-dependent Industries	County	739	33.37%	16.12%	9.51%	21.37%	31.79%	43.99%	62.75%
Panel D: Land Availability Quartile 4									
Protection Weighted Range Size Rarity (PWRSR)	County	758	0.57	1.89	0.00	0.03	0.11	0.30	2.54
Areas of Unprotected Biodiversity (AUBI)	County	758	0.02	0.05	0.00	0.00	0.00	0.01	0.10
Land Available (%)	County	758	0.96	0.02	0.92	0.95	0.97	0.98	0.99
Zillow Home Value Index	County × Month	70,931	156,108.27	83,650.99	68,837.50	102,793.18	137,769.67	185,652.40	303,504.58
Number of IRA & BIL Projects	County	758	0.19	1.06	0.00	0.00	0.00	0.00	1.00
Number of Conservation IRA & BIL Projects	County	758	0.06	0.63	0.00	0.00	0.00	0.00	0.00
Wage Share from Nature-dependent Industries	County	739	38.10%	16.92%	11.47%	25.57%	37.04%	50.42%	66.55%

Table IA.7: **Impact of Biodiversity Regulatory Risk on House Value Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and the log of Zillow Home Price Index within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). The sample period is from 2017 to 2024. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 includes counties with the least land available for building, while Quartile 4 includes those with the most. The first four columns (1) - (4) present regressions that only control for county, month, and state × year-month fixed effects. Columns (5) - (8) add in our full set of controls. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Zillow Home Price Index)							
	(1) Land Availability Quartile 1	(2) Land Availability Quartile 2	(3) Land Availability Quartile 3	(4) Land Availability Quartile 4	(5) Land Availability Quartile 1	(6) Land Availability Quartile 2	(7) Land Availability Quartile 3	(8) Land Availability Quartile 4
Post × Areas of Unprotected Biodiversity Importance	0.032*	0.054***	0.026	0.272**	0.036*	0.037*	0.012	0.371***
	(0.018)	(0.021)	(0.028)	(0.129)	(0.020)	(0.019)	(0.028)	(0.078)
Log(Employment)					0.085***	0.092***	0.105***	0.124***
					(0.015)	(0.025)	(0.031)	(0.036)
Post × Work From Home					-0.329***	-0.274***	-0.323***	-0.161
					(0.113)	(0.106)	(0.099)	(0.104)
Post × Climate Exposure Near Century					-0.148**	-0.361***	-0.015	0.245**
					(0.065)	(0.133)	(0.121)	(0.117)
Post × Climate Exposure Mid to Late Century					0.020	0.117***	0.064	0.103*
					(0.029)	(0.043)	(0.045)	(0.058)
Post × Habitat Climate Change Vulnerability Index					0.188*	0.311	-0.189	-0.414**
					(0.100)	(0.261)	(0.224)	(0.205)
Adj. R-squared	0.995	0.989	0.987	0.986	0.995	0.990	0.987	0.987
Obs.	73,836	72,602	70,711	70,451	52,384	65,172	67,194	68,111
County FEs	✓	✓	✓	✓	✓	✓	✓	✓
State × Year-Month FEs	✓	✓	✓	✓	✓	✓	✓	✓

Table IA.8: **Impact of Biodiversity Regulatory Risk on House Value Within Land Availability Quartiles - Log(AUBI)**

This table examines the relationship between the log of our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and the Log of Zillow Home Price Index within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). The sample period is from 2017 to 2024. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 has the least land available for building, while Quartile 4 has the most land available for building. Columns present regressions controlling for county, month, and state × year-month fixed effects and our controls. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Zillow Home Value Index)			
	(1) Land Availability Quartile 1	(2) Land Availability Quartile 2	(3) Land Availability Quartile 3	(4) Land Availability Quartile 4
Post × Log(Areas of Unprotected Biodiversity Importance)	-0.000	-0.000	0.003	0.010**
	(0.002)	(0.002)	(0.002)	(0.004)
Log(Employment)	0.084***	0.087***	0.121***	0.144*
	(0.017)	(0.030)	(0.031)	(0.074)
Post × Work From Home	-0.264**	-0.249***	0.063	0.138
	(0.127)	(0.095)	(0.134)	(0.222)
Post × Climate Exposure Near Century	-0.099	-0.136	0.016	0.097
	(0.089)	(0.181)	(0.186)	(0.253)
Post × Climate Exposure Mid to Late Century	0.013	0.159***	0.138**	0.107
	(0.036)	(0.049)	(0.059)	(0.134)
Post × Habitat Climate Change Vulnerability Index	0.183	-0.183	-0.426	-0.285
	(0.131)	(0.355)	(0.347)	(0.452)
Adj. R-squared	0.995	0.990	0.989	0.985
Obs.	40,097	46,645	37,938	22,692
County FEs	✓	✓	✓	✓
State × Year-Month FEs	✓	✓	✓	✓

Table IA.9: **Impact of Biodiversity Regulatory Risk on House Value Within Buildable Land Quartiles**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and the Log of Zillow Home Value Index within quartiles defined by Lutz and Sand (2023) buildable area measure (Equation 2). The sample period is from 2017 to 2024. We split counties into four quartiles based on their amount of buildable land available, constructed by taking the area in counties after removing developed land, parks, wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 has the least land available for building, while Quartile 4 has the most land available for building. The first four columns ((1) - (4)) present regressions only controlling for county, month, and state × year-month fixed effects. Columns (5) - (8) add in our COVID and climate related controls. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Zillow Home Value Index)							
	(1) Land Availability Quartile 1	(2) Land Availability Quartile 2	(3) Land Availability Quartile 3	(4) Land Availability Quartile 4	(5) Land Availability Quartile 1	(6) Land Availability Quartile 2	(7) Land Availability Quartile 3	(8) Land Availability Quartile 4
Post × Areas of Unprotected Biodiversity Importance	0.038	0.035	0.064*	0.283***	0.048*	0.022	0.051	0.287***
	(0.025)	(0.034)	(0.036)	(0.091)	(0.026)	(0.034)	(0.035)	(0.081)
Log(Employment)					0.049*	0.133***	0.158***	0.130**
					(0.028)	(0.030)	(0.039)	(0.060)
Post × Work From Home					-0.597***	-0.173*	-0.301***	0.037
					(0.121)	(0.094)	(0.079)	(0.165)
Post × Climate Exposure Near Century					0.025	-0.338***	-0.007	0.056
					(0.077)	(0.103)	(0.104)	(0.170)
Post × Climate Exposure Mid to Late Century					-0.050	0.109***	0.015	0.014
					(0.033)	(0.033)	(0.045)	(0.075)
Post × Habitat Climate Change Vulnerability Index					-0.106	0.480***	-0.135	-0.070
					(0.127)	(0.159)	(0.201)	(0.262)
Adj. R-squared	0.995	0.992	0.988	0.983	0.995	0.993	0.989	0.985
Obs.	47,473	47,426	46,808	46,895	36,239	40,511	41,999	45,237
County FEs	✓	✓	✓	✓	✓	✓	✓	✓
State × Year-Month FEs	✓	✓	✓	✓	✓	✓	✓	✓

Table IA.10: **Impact of Biodiversity Regulatory Risk on House Value - Quintile 5 vs Quintile 1 Within Land Availability Quartiles**

This table examines the relationship within Land Availability and our measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and the Log of Zillow Home Price Index (Equation 2). The sample period is from 2017 to 2024. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 has the least land available for building while Quartile 4 has the most land available for building. After splitting the sample by land availability, we then form treatment within each land availability quartile splitting into terciles where the top tercile of exposure in each land availability quartile is set equal to 1 and the bottom tercile is set equal to 0. Columns present regressions controlling for county, month, and state × year-month fixed effects and our controls. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Zillow Home Value Index)			
	(1) Land Availability Quartile 1	(2) Land Availability Quartile 2	(3) Land Availability Quartile 3	(4) Land Availability Quartile 4
Post × Quintile 5 vs Quintile 1 of Exposure Within Land Availability Quartile	0.035	0.026	0.000	0.054***
	(0.031)	(0.016)	(0.019)	(0.017)
Post × Work From Home	-0.432**	-0.156	-0.123	-0.030
	(0.208)	(0.136)	(0.194)	(0.209)
Post × Climate Exposure Near Century	0.000	-0.314	0.070	-0.011
	(0.143)	(0.227)	(0.205)	(0.240)
Post × Climate Exposure Mid to Late Century	0.002	0.117*	0.055	0.134
	(0.063)	(0.070)	(0.072)	(0.118)
Post × Habitat Climate Change Vulnerability Index	0.032	0.132	-0.406	-0.155
	(0.313)	(0.398)	(0.386)	(0.403)
Log(Employment)	0.113***	0.074**	0.066	0.231***
	(0.025)	(0.036)	(0.045)	(0.054)
Adj. R-squared	0.996	0.991	0.987	0.986
Obs.	20,319	25,158	25,785	26,308
County FEs	✓	✓	✓	✓
State × Year-Month FEs	✓	✓	✓	✓

Table IA.11: **Impact of Biodiversity Regulatory Risk on House Value Within Land Availability Quartiles Interacted With Wage Share of Nature-Intensive Industries**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity, our continuous measure of reliance on nature intensive industries, and the log of Zillow Home Price Index within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). The sample period is from 2017 to 2024. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 includes counties with the least land available for building, while Quartile 4 includes those with the most. Columns (1) - (4) add in our full set of controls as well as county, month, and state × year-month fixed effects. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Zillow Home Price Index)			
	(1) Land Availability Quartile 1	(2) Land Availability Quartile 2	(3) Land Availability Quartile 3	(4) Land Availability Quartile 4
Post × Areas of Unprotected Biodiversity Importance	0.047	0.041	0.006	0.753***
	(0.036)	(0.041)	(0.067)	(0.143)
Post × Areas of Unprotected Biodiversity Importance × Wage Share from Nature-dependent Industries	-0.037	-0.021	0.023	-1.140***
	(0.105)	(0.099)	(0.159)	(0.349)
Post × Wage Share from Nature-dependent Industries	-0.035	-0.018	0.007	0.008
	(0.026)	(0.024)	(0.025)	(0.023)
Log(Employment)	0.091***	0.100***	0.101***	0.128***
	(0.014)	(0.025)	(0.033)	(0.037)
Post × Work From Home	-0.386***	-0.331***	-0.293***	-0.170
	(0.117)	(0.114)	(0.111)	(0.113)
Post × Climate Exposure Mid to Late Century	0.009	0.119***	0.063	0.100*
	(0.029)	(0.043)	(0.045)	(0.058)
Post × Habitat Climate Change Vulnerability Index	0.176*	0.310	-0.148	-0.390*
	(0.102)	(0.261)	(0.226)	(0.215)
Adj. R-squared	0.995	0.990	0.987	0.987
Obs.	51,156	64,414	65,945	66,233
County FEs	✓	✓	✓	✓
State × Year-Month FEs	✓	✓	✓	✓

Table IA.12: **Excerpts of Project News from Local Media**

This table presents excerpts from local news articles retrieved from our Factiva search.

Project Name	**City**	**Excerpt**	**News Source**
Harold Simmons Park	Dallas, TX	"Located along a stretch of the Trinity River close to downtown, 200 acres of the urban green space will encompass a nature preserve. The other 50 acres—and for now, the key destinations imagined for the park—will feature four scenic overlooks that crest the levees on either side. All that action will take place between the Margaret McDermott Bridge and Ronald Kirk Bridge."	Dallas Innovates
Downtown Gateway and Greenway	Grand Forks, ND	"...features of this phase in the preliminary plans include the GFK Gateway monument, a sloped lawn and amphitheater, the obelisk terrace with river access, ADA access to the top of the levee, play landforms and vernal pools, and restoration of the natural riverbank."	Grand Forks Herald
Whitewater Park	Bowling Green, KY	"A new phase of Bowling Green's Riverfront Park master plan is now underway due to a $3.64 million grant awarded by the National Park Service, funding a new whitewater park to be built on the Barren River near downtown...The proposed park will cover roughly 4,000 feet of the Barren River, stretching from BGMU's water treatment plant past College Street. According to Childers, the design will improve recreation opportunities and add more safety to the river's accessibility."	City of Bowling Green
Downtown Greenway	Gadsden, AL	"The Downtown Gadsden Greenway project will be a multiuse urban nature trail paralleling Tuscaloosa Avenue and connecting the Black Creek Trail System. The greenway will be constructed on a retired railbed, with the city planning to acquire additional property along Black Creek to connect the greenway to the James D. Martin Wildlife Park behind Gadsden Mall. The project will ultimately create a trail loop around the city's urban core...Along the trail, residents will be able to engage in the community's diverse ecosystem along with having access to its waterways, sports parks, schools, public transportation facilities, community centers, grocery stores, healthcare services and neighborhoods."	Alabama News Center
Patton Park & Fall Line Trail	Petersburg, VA	"Patton Park... will be the intersection of the east-west Appomattox River Trail and the north-south Fall Line Trail, a 43-mile walking and bike trail between Petersburg and Ashland."	The Progress Index

Table IA.13: **Impact of Biodiversity Regulatory Risk on Land Values Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and land value measures from Davis et al. (2021) within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). Land value measures from Davis et al. (2021) are derived using Uniform Residential Appraisal Report submissions to the Government Sponsored Enterprises (GSEs), Fannie Mae and Freddie Mac and then subtracting an estimate of depreciated replacement cost of the housing structure. The sample period is from 2017 to 2022. Land values are at the county × year level. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 includes counties with the least land available for building, while Quartile 4 includes those with the most. The first four columns (1) - (4) present regressions that only control for county, month, and state × year fixed effects. Columns (5) - (8) add in our full set of controls. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Land Value Per Acre)							
	(1) Land Availability Quartile 1	(2) Land Availability Quartile 2	(3) Land Availability Quartile 3	(4) Land Availability Quartile 4	(5) Land Availability Quartile 1	(6) Land Availability Quartile 2	(7) Land Availability Quartile 3	(8) Land Availability Quartile 4
Post × Areas of Unprotected Biodiversity Importance	-0.052	0.042	0.116	0.504***	0.014	0.025	0.035	0.462***
	(0.064)	(0.053)	(0.074)	(0.177)	(0.061)	(0.048)	(0.072)	(0.152)
Log(Employment)					0.562***	1.009***	0.534***	0.497***
					(0.142)	(0.138)	(0.116)	(0.161)
Post × Work From Home					-0.477**	-0.265	0.242	0.181
					(0.236)	(0.229)	(0.177)	(0.282)
Post × Climate Exposure Near Century					-0.022	-0.018	0.129	1.167**
					(0.211)	(0.416)	(0.336)	(0.581)
Post × Climate Exposure Mid to Late Century					0.008	0.030	0.001	-0.166
					(0.081)	(0.113)	(0.132)	(0.168)
Post × Habitat Climate Change Vulnerability Index					0.093	-0.227	-0.723	-1.356
					(0.247)	(0.748)	(0.653)	(0.996)
Adj. R-squared	0.995	0.992	0.992	0.987	0.995	0.993	0.993	0.988
Obs.	1,944	1,686	1,572	954	1,596	1,566	1,548	942
County FEs	✓	✓	✓	✓	✓	✓	✓	✓
State × Year FEs	✓	✓	✓	✓	✓	✓	✓	✓

Table IA.14: **Impact of Biodiversity Regulatory Risk on Property Values Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and property values from Davis et al. (2021) within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). Property value measures from Davis et al. (2021) are derived using Uniform Residential Appraisal Report submissions to the Government Sponsored Enterprises (GSEs), Fannie Mae and Freddie Mac. The sample period is from 2017 to 2022. Property values are at the county $\times$ year level. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 has the least land available for building while Quartile 4 has the most land available for building. The first four columns ((1) - (4)) present regressions only controlling for county, month, and state $\times$ year fixed effects. Columns (5) - (8) add in our COVID and climate related controls. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Property Value)							
	(1) Land Availability Quartile 1	(2) Land Availability Quartile 2	(3) Land Availability Quartile 3	(4) Land Availability Quartile 4	(5) Land Availability Quartile 1	(6) Land Availability Quartile 2	(7) Land Availability Quartile 3	(8) Land Availability Quartile 4
Post $\times$ Areas of Unprotected Biodiversity Importance	-0.045	0.020	0.024	0.314***	-0.021	0.022	0.013	0.295***
	(0.033)	(0.028)	(0.037)	(0.094)	(0.035)	(0.026)	(0.037)	(0.084)
Log(Employment)					0.154**	0.334***	0.183***	0.170**
					(0.076)	(0.085)	(0.051)	(0.076)
Post $\times$ Work From Home					-0.628***	-0.634***	-0.478***	0.048
					(0.137)	(0.118)	(0.112)	(0.128)
Post $\times$ Climate Exposure Near Century					-0.027	-0.101	0.042	0.484**
					(0.092)	(0.280)	(0.185)	(0.229)
Post $\times$ Climate Exposure Mid to Late Century					0.021	0.026	0.032	0.016
					(0.040)	(0.044)	(0.052)	(0.091)
Post $\times$ Habitat Climate Change Vulnerability Index					0.085	0.088	-0.242	-0.712**
					(0.117)	(0.500)	(0.360)	(0.359)
Adj. R-squared	0.995	0.991	0.991	0.990	0.995	0.992	0.992	0.991
Obs.	1,944	1,686	1,572	954	1,596	1,566	1,548	942
County FEs	✓	✓	✓	✓	✓	✓	✓	✓
State $\times$ Year FEs	✓	✓	✓	✓	✓	✓	✓	✓

Table IA.15: **Impact of Biodiversity Regulatory Risk on Investment and Residential Loan Amount Applied For Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and the sum of HMDA mortgages applied for in a county overall and by purpose within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). HMDA loans are at the county × year level. Investment loans are loans in which occupancy type is reported as investment. Primary residence loans are loans in which occupancy type is reported as "primary residence." Secondary residence loans are loans in which occupancy type is reported as "secondary residence." The sample period is from 2017 to 2023. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 has the least land available for building while Quartile 4 has the most land available for building. All regressions are run using our full set of controls and county as well as state × year fixed effects. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Loan Amount Applied For)			
	(1) Land Availability Quartile 1	(2) Land Availability Quartile 2	(3) Land Availability Quartile 3	(4) Land Availability Quartile 4
Panel A: All Loans				
Post × Areas of Unprotected Biodiversity Importance	0.022	-0.063	0.046	0.288**
	(0.051)	(0.040)	(0.055)	(0.131)
Post × Work From Home	-1.312***	-1.328***	-1.803***	-1.115***
	(0.214)	(0.186)	(0.168)	(0.208)
Post × Climate Exposure Near Century	0.050	0.170	-0.032	0.011
	(0.162)	(0.232)	(0.241)	(0.279)
Post × Climate Exposure Mid to Late Century	-0.051	0.069	-0.199**	0.045
	(0.068)	(0.074)	(0.090)	(0.111)
Post × Habitat Climate Change Vulnerability Index	0.063	-0.210	0.458	0.064
	(0.220)	(0.437)	(0.456)	(0.486)
Log(Employment)	0.048	-0.155*	0.012	0.130
	(0.138)	(0.084)	(0.114)	(0.089)
Adj. R-squared	0.996	0.995	0.995	0.994
Obs.	3,264	3,891	3,738	3,277
County FEs	✓	✓	✓	✓
State × Year FEs	✓	✓	✓	✓
Panel B: Investment Loans				
Post × Areas of Unprotected Biodiversity Importance	0.083	0.315**	0.220	0.929**
	(0.145)	(0.136)	(0.154)	(0.407)
Post × Work From Home	-1.335**	-1.145**	-2.036***	-0.533
	(0.570)	(0.567)	(0.428)	(0.545)
Post × Climate Exposure Near Century	-0.019	-0.983	-0.388	1.057
	(0.448)	(0.850)	(0.716)	(0.887)
Post × Climate Exposure Mid to Late Century	0.035	0.802***	0.421*	-0.016
	(0.186)	(0.287)	(0.233)	(0.357)
Post × Habitat Climate Change Vulnerability Index	0.198	0.217	0.021	-1.795
	(0.639)	(1.497)	(1.339)	(1.750)
Log(Employment)	0.527*	-0.367	-0.030	-0.323
	(0.292)	(0.327)	(0.266)	(0.393)
Adj. R-squared	0.959	0.944	0.950	0.933
Obs.	3,264	3,891	3,738	3,277
County FEs	✓	✓	✓	✓
State × Year FEs	✓	✓	✓	✓
Panel C: Primary Residence Loans				
Post × Areas of Unprotected Biodiversity Importance	0.008	-0.101**	0.012	0.218
	(0.048)	(0.040)	(0.059)	(0.141)
Post × Work From Home	-1.531***	-1.509***	-1.847***	-1.280***
	(0.260)	(0.192)	(0.176)	(0.217)
Post × Climate Exposure Near Century	-0.096	0.206	0.118	-0.047
	(0.160)	(0.235)	(0.256)	(0.285)
Post × Climate Exposure Mid to Late Century	-0.041	0.058	-0.211**	0.012
	(0.070)	(0.076)	(0.096)	(0.115)
Post × Habitat Climate Change Vulnerability Index	0.261	-0.239	0.188	0.262
	(0.231)	(0.448)	(0.477)	(0.501)
Log(Employment)	0.024	-0.094	0.030	0.180**
	(0.136)	(0.097)	(0.113)	(0.091)
Adj. R-squared	0.996	0.995	0.995	0.994
Obs.	3,264	3,891	3,738	3,277
County FEs	✓	✓	✓	✓
State × Year FEs	✓	✓	✓	✓
Panel D: Secondary Residence Loans				
Post × Areas of Unprotected Biodiversity Importance	-0.091	-0.037	-0.059	-0.028
	(0.104)	(0.136)	(0.246)	(0.454)
Post × Work From Home	-1.341***	-0.566	-2.297***	-0.760
	(0.415)	(0.484)	(0.475)	(0.629)
Post × Climate Exposure Near Century	-0.196	-0.002	-0.434	-1.030
	(0.374)	(0.608)	(0.785)	(0.838)
Post × Climate Exposure Mid to Late Century	0.118	-0.154	-0.264	0.571
	(0.159)	(0.215)	(0.285)	(0.418)
Post × Habitat Climate Change Vulnerability Index	0.304	0.312	0.845	1.807
	(0.524)	(1.132)	(1.424)	(1.444)
Log(Employment)	-0.123	-0.078	-0.243	-0.260
	(0.308)	(0.289)	(0.328)	(0.340)
Adj. R-squared	0.972	0.938	0.926	0.871
Obs.	3,264	3,891	3,738	3,277
County FEs	✓	✓	✓	✓
State × Year FEs	✓	✓	✓	✓

Table IA.16: **Impact of Biodiversity Regulatory Risk on Investment and Residential Loan Amount Originated Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and the sum of HMDA mortgages originated in a county overall and by purpose within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). HMDA loans are at the county $\times$ year level. Investment loans are loans in which occupancy type is reported as investment. Primary residence loans are loans in which occupancy type is reported as "primary residence." Secondary residence loans are loans in which occupancy type is reported as "secondary residence." The sample period is from 2017 to 2023. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 has the least land available for building while Quartile 4 has the most land available for building. All regressions are run using our full set of controls and county as well as state $\times$ year fixed effects. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Loan Amount Originated)			
	(1) Land Availability Quartile 1	(2) Land Availability Quartile 2	(3) Land Availability Quartile 3	(4) Land Availability Quartile 4
Panel A: All Loans				
Post × Areas of Unprotected Biodiversity Importance	0.021	-0.063	0.040	0.370***
	(0.055)	(0.042)	(0.059)	(0.142)
Post × Work From Home	-1.219***	-1.288***	-1.703***	-1.188***
	(0.224)	(0.192)	(0.160)	(0.204)
Post × Climate Exposure Near Century	0.033	-0.064	0.001	-0.024
	(0.170)	(0.239)	(0.239)	(0.294)
Post × Climate Exposure Mid to Late Century	-0.036	0.177**	-0.151*	0.009
	(0.067)	(0.077)	(0.090)	(0.116)
Post × Habitat Climate Change Vulnerability Index	0.081	0.006	0.230	0.249
	(0.230)	(0.450)	(0.443)	(0.520)
Log(Employment)	0.032	-0.176*	0.094	0.159*
	(0.136)	(0.097)	(0.115)	(0.089)
Adj. R-squared	0.996	0.995	0.995	0.994
Obs.	3,264	3,891	3,738	3,277
County FEs	✓	✓	✓	✓
State × Year FEs	✓	✓	✓	✓
Panel B: Investment Loans				
Post × Areas of Unprotected Biodiversity Importance	0.124	0.416***	0.218	0.994**
	(0.151)	(0.151)	(0.167)	(0.422)
Post × Work From Home	-1.193**	-1.245**	-1.946***	-0.496
	(0.596)	(0.590)	(0.428)	(0.562)
Post × Climate Exposure Near Century	-0.333	-1.110	-0.548	1.285
	(0.471)	(0.867)	(0.744)	(0.904)
Post × Climate Exposure Mid to Late Century	0.131	0.755**	0.370	-0.095
	(0.192)	(0.312)	(0.242)	(0.356)
Post × Habitat Climate Change Vulnerability Index	0.454	0.470	0.595	-1.981
	(0.692)	(1.489)	(1.407)	(1.789)
Log(Employment)	0.469	-0.632*	-0.150	-0.194
	(0.325)	(0.344)	(0.291)	(0.402)
Adj. R-squared	0.957	0.938	0.946	0.930
Obs.	3,264	3,891	3,738	3,277
County FEs	✓	✓	✓	✓
State × Year FEs	✓	✓	✓	✓
Panel C: Primary Residence Loans				
Post × Areas of Unprotected Biodiversity Importance	-0.000	-0.105**	0.007	0.291*
	(0.055)	(0.043)	(0.064)	(0.170)
Post × Work From Home	-1.461***	-1.452***	-1.744***	-1.314***
	(0.272)	(0.188)	(0.166)	(0.208)
Post × Climate Exposure Near Century	-0.159	-0.006	0.145	-0.145
	(0.185)	(0.238)	(0.252)	(0.307)
Post × Climate Exposure Mid to Late Century	-0.018	0.178**	-0.164*	-0.050
	(0.072)	(0.080)	(0.098)	(0.122)
Post × Habitat Climate Change Vulnerability Index	0.360	-0.085	-0.047	0.634
	(0.273)	(0.449)	(0.460)	(0.548)
Log(Employment)	-0.003	-0.087	0.138	0.221**
	(0.137)	(0.089)	(0.116)	(0.091)
Adj. R-squared	0.995	0.995	0.995	0.993
Obs.	3,264	3,891	3,738	3,277
County FEs	✓	✓	✓	✓
State × Year FEs	✓	✓	✓	✓
Panel D: Secondary Residence Loans				
Post × Areas of Unprotected Biodiversity Importance	-0.092	0.050	0.055	-0.318
	(0.113)	(0.147)	(0.263)	(0.495)
Post × Work From Home	-1.363***	-0.805	-2.710***	-0.975
	(0.462)	(0.491)	(0.510)	(0.718)
Post × Climate Exposure Near Century	-0.180	-0.508	-0.158	-0.972
	(0.387)	(0.674)	(0.881)	(0.853)
Post × Climate Exposure Mid to Late Century	0.147	-0.109	-0.205	0.658
	(0.167)	(0.226)	(0.299)	(0.421)
Post × Habitat Climate Change Vulnerability Index	0.295	1.234	0.386	1.303
	(0.549)	(1.277)	(1.627)	(1.508)
Log(Employment)	-0.149	-0.240	-0.191	-0.237
	(0.315)	(0.306)	(0.335)	(0.328)
Adj. R-squared	0.970	0.934	0.920	0.861
Obs.	3,264	3,891	3,738	3,277
County FEs	✓	✓	✓	✓
State × Year FEs	✓	✓	✓	✓

Table IA.17: **Impact of Biodiversity Regulatory Risk on Park Visits Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and park visits from Google Mobility data within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). Google Mobility data are created with aggregated, anonymized sets of data from users who have turned on the Location History setting. The sample period is from 2020 to 2022. Mobility reports are at the county × year level and the change is referenced to a baseline in 2019. Parks categories is defined as "places like local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens." We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 includes counties with the least land available for building, while Quartile 4 includes those with the most. The first four columns (1) - (4) present regressions that only control for county, month, and state × year fixed effects. Columns (5) - (8) add in our full set of controls. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Yearly Average Change in Park Visits (%)							
	(1) Land Availability Quartile 1	(2) Land Availability Quartile 2	(3) Land Availability Quartile 3	(4) Land Availability Quartile 4	(5) Land Availability Quartile 1	(6) Land Availability Quartile 2	(7) Land Availability Quartile 3	(8) Land Availability Quartile 4
Post × Areas of Unprotected Biodiversity Importance	-2.182	6.105	-10.445	27.911*	5.724	10.856	-8.608	36.070**
	(6.367)	(6.575)	(6.484)	(14.848)	(6.364)	(7.129)	(7.228)	(15.380)
Log(Employment)					-17.967	-2.401	28.575	-15.078
					(26.849)	(26.475)	(24.480)	(30.292)
Post × Work From Home					-98.945***	-13.433	-29.343	-36.068
					(24.663)	(20.594)	(28.296)	(34.879)
Post × Climate Exposure Near Century					-24.960	-63.727	-13.925	-63.643
					(21.171)	(45.025)	(49.253)	(69.208)
Post × Climate Exposure Mid to Late Century					24.997***	-14.113	3.887	-24.586
					(8.685)	(9.493)	(10.158)	(20.566)
Post × Habitat Climate Change Vulnerability Index					25.108	152.014	40.208	231.217
					(28.953)	(96.243)	(91.064)	(145.845)
Adj. R-squared	0.939	0.953	0.953	0.946	0.944	0.953	0.951	0.949
Obs.	1,048	732	660	378	851	672	648	369
County FEs	✓	✓	✓	✓	✓	✓	✓	✓
State × Year FEs	✓	✓	✓	✓	✓	✓	✓	✓

Table IA.18: **Impact of Biodiversity Regulatory Risk on Building Permits Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and building permit data from the Census building permits survey within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). The sample period is from 2017 to 2024. We use three measures from the building permits survey as outcomes. A housing unit is a house, an apartment, a group of rooms or a single room intended for occupancy as separate living quarters. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 has the least land available for building while Quartile 4 has the most land available for building. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Buildings)				Log(Units)				Log(Value)			
	(1) Land Availability Quartile 1	(2) Land Availability Quartile 2	(3) Land Availability Quartile 3	(4) Land Availability Quartile 4	(5) Land Availability Quartile 1	(6) Land Availability Quartile 2	(7) Land Availability Quartile 3	(8) Land Availability Quartile 4	(9) Land Availability Quartile 1	(10) Land Availability Quartile 2	(11) Land Availability Quartile 3	(12) Land Availability Quartile 4
Post × Areas of Unprotected Biodiversity Importance	0.213	-0.293	-0.144	0.138	0.171	-0.233	-0.313	0.301	0.134	-0.372	-0.309	0.238
	(0.231)	(0.238)	(0.267)	(0.665)	(0.248)	(0.254)	(0.285)	(0.652)	(0.255)	(0.248)	(0.265)	(0.678)
Log(Employment)	-0.545	-0.059	0.143	0.319	-0.597	0.055	0.045	0.519	-0.340	0.177	0.169	0.110
	(0.398)	(0.372)	(0.322)	(0.270)	(0.394)	(0.380)	(0.336)	(0.317)	(0.407)	(0.395)	(0.361)	(0.364)
Post × Work From Home	-2.597***	-1.773**	-2.605***	-0.631	-2.968***	-0.949	-2.217***	-0.604	-2.952***	-1.911**	-3.061***	-0.884
	(0.773)	(0.743)	(0.627)	(0.798)	(0.792)	(0.788)	(0.708)	(0.951)	(0.792)	(0.830)	(0.687)	(0.939)
Post × Climate Exposure Near Century	-0.631	-0.146	1.534*	0.683	-0.609	0.028	1.850**	0.736	-1.060	-0.058	1.673*	1.241
	(0.654)	(1.016)	(0.864)	(1.004)	(0.679)	(1.021)	(0.846)	(1.079)	(0.782)	(1.060)	(0.960)	(1.117)
Post × Climate Exposure Mid to Late Century	0.153	0.463	-0.200	0.975**	0.236	0.495	-0.251	0.793	0.242	0.405	-0.667*	0.611
	(0.313)	(0.368)	(0.341)	(0.485)	(0.317)	(0.386)	(0.371)	(0.525)	(0.342)	(0.395)	(0.359)	(0.524)
Post × Habitat Climate Change Vulnerability Index	1.338	-0.510	-3.015*	-2.057	1.074	-0.943	-3.729**	-1.678	1.920*	-0.362	-2.317	-2.340
	(0.857)	(1.956)	(1.619)	(1.638)	(0.869)	(1.942)	(1.582)	(1.753)	(1.000)	(2.002)	(1.746)	(1.902)
Adj. R-squared	0.912	0.911	0.929	0.916	0.917	0.905	0.921	0.902	0.917	0.909	0.927	0.899
Obs.	3,392	3,956	4,219	4,143	3,392	3,956	4,219	4,143	3,392	3,958	4,219	4,144
County FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State × Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table IA.19: **Impact of Biodiversity Regulatory Risk on Building Permits Within Land Availability Quartiles Using Imputed Values**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and building permit data from the Census building permits survey within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). The sample period is from 2017 to 2024. We use three measures from the building permits survey as outcomes. In columns (1)-(4) we use as our outcome the log of the number of building permits imputed in each county in each year. In columns (5)-(8) we use as our outcome the log of the number of units, a housing unit is a house, an apartment, a group of rooms or a single room intended for occupancy as separate living quarters. In columns (9)-(12) as our outcome the log of the value of construction in a county. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 has the least land available for building while Quartile 4 has the most land available for building. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Buildings)				Log(Units)				Log(Value)			
	(1) Land Availability Quartile 1	(2) Land Availability Quartile 2	(3) Land Availability Quartile 3	(4) Land Availability Quartile 4	(5) Land Availability Quartile 1	(6) Land Availability Quartile 2	(7) Land Availability Quartile 3	(8) Land Availability Quartile 4	(9) Land Availability Quartile 1	(10) Land Availability Quartile 2	(11) Land Availability Quartile 3	(12) Land Availability Quartile 4
Post × Areas of Unprotected Biodiversity Importance	0.184	-0.164	-0.179	-0.459	0.139	-0.112	-0.356	-0.476	0.142	-0.248	-0.370	-0.679
	(0.156)	(0.167)	(0.230)	(0.548)	(0.152)	(0.177)	(0.247)	(0.554)	(0.165)	(0.187)	(0.230)	(0.520)
Log(Employment)	-0.203	0.022	0.378	0.819***	-0.135	0.133	0.248	0.888***	-0.117	0.153	0.486*	0.582*
	(0.324)	(0.308)	(0.236)	(0.257)	(0.304)	(0.323)	(0.246)	(0.301)	(0.288)	(0.321)	(0.275)	(0.341)
Post × Work From Home	-1.965***	-2.360***	-1.425***	-0.679	-2.164***	-1.892***	-0.819	-0.050	-2.400***	-2.534***	-1.760***	-0.367
	(0.707)	(0.578)	(0.547)	(0.625)	(0.716)	(0.599)	(0.640)	(0.725)	(0.691)	(0.667)	(0.642)	(0.742)
Post × Climate Exposure Near Century	-0.260	-0.331	0.948	0.268	-0.171	-0.284	1.072	0.308	-0.558	0.020	1.071	1.181
	(0.503)	(0.764)	(0.694)	(0.848)	(0.472)	(0.785)	(0.716)	(0.937)	(0.523)	(0.848)	(0.831)	(0.996)
Post × Climate Exposure Mid to Late Century	-0.146	0.756**	-0.296	0.773**	-0.084	0.799***	-0.226	0.661	-0.055	0.674**	-0.508	0.363
	(0.229)	(0.293)	(0.286)	(0.390)	(0.219)	(0.309)	(0.325)	(0.430)	(0.224)	(0.312)	(0.317)	(0.441)
Post × Habitat Climate Change Vulnerability Index	0.472	-0.316	-1.714	-1.115	0.211	-0.549	-2.126	-0.908	0.775	-0.925	-1.496	-2.108
	(0.668)	(1.338)	(1.277)	(1.534)	(0.617)	(1.393)	(1.312)	(1.682)	(0.704)	(1.473)	(1.489)	(1.900)
Adj. R-squared	0.957	0.950	0.956	0.940	0.957	0.944	0.945	0.925	0.960	0.944	0.949	0.921
Obs.	3,631	4,388	4,614	4,459	3,631	4,388	4,614	4,459	3,630	4,387	4,607	4,460
County FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State × Year FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table IA.20: **Impact of Biodiversity Regulatory Risk Exposure on Standardized Land Values Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and land value measures from Davis et al. (2021) within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). Land value measures from Davis et al. (2021) are derived using Uniform Residential Appraisal Report submissions to the Government Sponsored Enterprises (GSEs), Fannie Mae and Freddie Mac. Standardized estimates report the price of land per quarter-acre after adjusting for the fact that the price of land per acre tends to fall as acreage increases. Land values are at the county $\times$ year level. The sample period is from 2017 to 2022. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 has the least land available for building while Quartile 4 has the most land available for building. The first four columns ((1) - (4)) present regressions only controlling for county, month, and state $\times$ year fixed effects. Columns (5) - (8) add in our COVID and climate related controls. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Land Value Standardized)							
	(1) Land Availability Quartile 1	(2) Land Availability Quartile 2	(3) Land Availability Quartile 3	(4) Land Availability Quartile 4	(5) Land Availability Quartile 1	(6) Land Availability Quartile 2	(7) Land Availability Quartile 3	(8) Land Availability Quartile 4
Post $\times$ Areas of Unprotected Biodiversity Importance	-0.052	0.041	0.123*	0.509***	0.016	0.024	0.048	0.448***
	(0.065)	(0.052)	(0.074)	(0.167)	(0.062)	(0.047)	(0.073)	(0.140)
Log(Employment)					0.570***	1.031***	0.563***	0.553***
					(0.147)	(0.138)	(0.118)	(0.165)
Post $\times$ Work From Home					-0.415*	-0.142	0.292*	0.218
					(0.239)	(0.225)	(0.177)	(0.297)
Post $\times$ Climate Exposure Near Century					-0.078	-0.023	0.111	1.240**
					(0.209)	(0.375)	(0.324)	(0.586)
Post $\times$ Climate Exposure Mid to Late Century					0.028	0.015	0.045	-0.148
					(0.084)	(0.111)	(0.124)	(0.169)
Post $\times$ Habitat Climate Change Vulnerability Index					0.165	-0.195	-0.696	-1.584
					(0.248)	(0.673)	(0.615)	(0.988)
Adj. R-squared	0.992	0.988	0.987	0.979	0.992	0.989	0.988	0.980
Obs.	1,944	1,686	1,572	954	1,596	1,566	1,548	942
County FEs	✓	✓	✓	✓	✓	✓	✓	✓
State $\times$ Year FEs	✓	✓	✓	✓	✓	✓	✓	✓

Table IA.21: **Impact of Biodiversity Regulatory Risk on Standardized Property Values Within Land Availability Quartiles**

This table examines the relationship between our continuous measure of biodiversity regulatory risk using Areas of Unprotected Biodiversity and standardized property values from Davis et al. (2021) within quartiles defined by Lutz and Sand (2023) land availability measure (Equation 2). Property value measures from Davis et al. (2021) are derived using Uniform Residential Appraisal Report submissions to the Government Sponsored Enterprises (GSEs), Fannie Mae and Freddie Mac. Standardized estimates report the price after adjusting for the fact that value of property tends to fall as acreage increases. Property values are at the county $\times$ year level. The sample period is from 2017 to 2022. We split counties into four quartiles based on their amount of land available, constructed by taking the area in counties after removing wetlands, water areas, and very high slope land and dividing by total area. Quartile 1 has the least land available for building while Quartile 4 has the most land available for building. The first four columns ((1) - (4)) present regressions only controlling for county, month, and state $\times$ year fixed effects. Columns (5) - (8) add in our COVID and climate related controls. Standard errors are clustered at the county level and are reported in parentheses. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

	Log(Property Value Standardized)							
	(1) Land Availability Quartile 1	(2) Land Availability Quartile 2	(3) Land Availability Quartile 3	(4) Land Availability Quartile 4	(5) Land Availability Quartile 1	(6) Land Availability Quartile 2	(7) Land Availability Quartile 3	(8) Land Availability Quartile 4
Post $\times$ Areas of Unprotected Biodiversity Importance	-0.042	0.008	0.026	0.284***	-0.016	0.007	0.014	0.258***
	(0.031)	(0.023)	(0.036)	(0.090)	(0.034)	(0.022)	(0.036)	(0.079)
Log(Employment)					0.154**	0.311***	0.215***	0.201***
					(0.068)	(0.072)	(0.050)	(0.070)
Post $\times$ Work From Home					-0.680***	-0.497***	-0.428***	-0.022
					(0.129)	(0.108)	(0.099)	(0.111)
Post $\times$ Climate Exposure Near Century					-0.043	-0.130	0.022	0.471**
					(0.082)	(0.235)	(0.169)	(0.207)
Post $\times$ Climate Exposure Mid to Late Century					0.033	0.020	0.021	0.019
					(0.037)	(0.041)	(0.048)	(0.089)
Post $\times$ Habitat Climate Change Vulnerability Index					0.097	0.123	-0.161	-0.783**
					(0.102)	(0.421)	(0.327)	(0.360)
Adj. R-squared	0.995	0.993	0.992	0.990	0.996	0.994	0.992	0.991
Obs.	1,944	1,686	1,572	954	1,596	1,566	1,548	942
County FEs	✓	✓	✓	✓	✓	✓	✓	✓
State $\times$ Year FEs	✓	✓	✓	✓	✓	✓	✓	✓